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AFIT/GLM/LSM/88S-10

AN ALTERNATIVE FORECASTING

METHOD FOR DRIVE

THESIS

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AN ALTERNATIVE FORECASTING METHOD FOR DRIVE

THESIS

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Master of Science in Logistics Management

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Preface

The purpose of this study was to determine if the DRIVE model is sensitive to varying demand rates by base. This study was designed to facilitate further analysis of DRIVE's forecasting method.

DRIVE uses a four-quarter moving average of worldwide demands to predict base demands. The current DRIVE model was used to forecast base demands for the third and fourth quarters of 1987. Then the DRIVE algorithm was changed to predict base demands by using an 18 month moving average of base demands. The quarterly depot repair lists DRIVE produced using both forecasting methods indicated that DRIVE is sensitive to varying demand rates by base.

This research would not have been possible without the help from others. I wish to thank my faculty advisor, Lt Col Bruce Christensen, for his encouragement and assistance in times of need. I also wish to thank Richard Moore, Barb Wieland, and Bob McKormick of the AFLC Programs Assessment Division for their guidance and cooperation in performing this research. Finally, I wish to thank my wife [redacted] for her understanding and concern throughout this research effort.

Alan J. Closson

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Abstract

The purpose of this ~~study~~ was to determine the effect of using base specific demand rates in the DRIVE model. There were two research objectives: (1) Determine if DRIVE's repair priorities significantly change due to demand variations. (2) Determine how DRIVE's repair priorities change by using base specific demand rates instead of worldwide demand rates.

This study compared the quarterly repair lists DRIVE recommended using worldwide demands versus base demands for the F-16A. Several depot repair hour constraints were used to see how the repair lists changed given different manhour constraints. The research revealed that using base specific demands (D028) in the DRIVE model instead of worldwide demands (D041) significantly changes the quarterly depot repair priorities. For the third and fourth quarters of 1987, the D028 forecasts recommended less quantities of the critical LRUs for repair but did not recommend less quantities of SRUs for repair across all of the critical SRUs. The D028 forecasts also required fewer repair hours to satisfy the optimal number of LRUs DRIVE recommended for repair. This may be a result of incomplete D028 data; the bases with no D028 demands may have reduced the repair requirement beyond the

level their actual demands would have recommended. The repair quantities of LRUs and SRUs based on the D028 demand rates also vary less than the D041 repair quantities from one quarter to the next. This indicates that the D028 18 month moving average forecasts are less variable than DRIVE's four-quarter moving average forecast.

There is considerable variation between D028 base demand rates; however, the D028 demand rate at a base remains relatively stable between quarters. The D028 18 month moving average appears to dampen the actual base demand rates. These observations are consistent across all of the LRUs and SRUs at each of the 21 F-16 bases. Since the worldwide demand rates are an average of all of the base's demands, the requirements of the bases with unusually high demands are not met, while the bases with low demands can not justify the requirements that the worldwide demand rates set for them. By taking an average of the highly different base demand rates, the DRIVE model does not properly allocate requirements according to each base's demand history.

AN ALTERNATIVE FORECASTING METHOD FOR DRIVE

I. Introduction

Readiness and sustainability have received increased attention by military planners over the past two decades. Recent budget restrictions have increased the importance of relating resources to readiness. Readiness is defined as being prepared for action or being prompt to react. Abell defines military readiness as the ability of military forces to perform their mission (Abell, 1981:16). The Air Force is concerned with how responsive a military force is and how sustainable it is over time. An example of the former is an air-defense force's capability to respond quickly to an aerial attack. An example of the latter is the effectiveness of tactical fighters over an extended interdictive campaign (Abell, 1981:16).

The problem of relating resources to readiness is not new. At the May 1974 Logistics Research Conference, then Deputy Chief of Naval Operations (Logistics) Vice Admiral Walter D. Gaddis, USN, clearly addressed the problem.

> An example is our need for a simple, usable definition of material readiness of Naval forces, a means of measuring it, and some perfectly definite input-output relationships. We need to be able to link resource inputs, and this means money, to any of the numerous potential outputs, and these mean military

applications. We need to be able to predict not only <u>how much</u> readiness measure will change, but also <u>when</u> it will change, as a result of changes in inputs (Monahan, 1981:11).

In the 1978 Defense Authorization Act, Congress specified the need for relating resources to operational capability. The act required future DOD budgets to include data that projects the effect requested appropriations will have on readiness (Abell, 1981:15).

This poses several problems for the Department of Defense. First, there are no historical data that reflect the impact of resources on readiness. Second, it is difficult to understand dynamic interactions of the allocation, expenditure, and commitment of resources and their resulting effect on readiness (Abell, 1981:15). Third, until now there have been no means of relating specific resources to changes in combat capability.

Motivation

The Air Force has spent much time and many resources analyzing how resource requirements relate to combat capability. Part of this research involves integrating the logistics support system to wartime environments. A Project Air Force study conducted by the Rand Corporation in 1984 - <u>Enhancing the Integration and Responsiveness of the Logistics Support System to Meet Wartime and Peacetime Uncertainties</u> - was concerned with how to best counter the major environmental

and demand rate uncertainties that complicate logistics operations and resource allocation in peacetime and wartime. The research identified the nature and source of uncertainties and how logistic resources could be coordinated to overcome them (Rand, 1984).

Rand's Project Air Force involves several other studies that have investigated "potentially serious problems that underlie current estimates of the wartime demand for logistics support" (Rand, 1984:2). The Driving Inputs and Assumptions of Stockage/Assessment Models (Rand, 1982b) discovered unexpectedly high levels of demand variability from base to base and at any given base across time. Rand has accumulated much information on additional complexities arising from enemy attacks on our airbases in Sortie Production in Dynamic Wartime Environments (Rand, 1982a). These studies have given us important information on the characteristics, causes, and implications of uncertainties in our logistics system. They also indicate that the logistics support system must be able to adapt to uncertainties and varying demand rates. The flexibility and responsiveness of the logistics support system needs to be increased to better utilize the assets we have (Rand, 1984:3).

Initiatives along these lines, emerging from Rand's Project Air Force work, are called CLOUT (Coupling Logistics to Operations to meet Uncertainties and the Threat). The CLOUT initiatives involve enhancing logistics systems in the

theater, at the depots, and within command and control systems. They also include better ways to identify and react to varying demand in capability assessment models and spares requirements determinations (Rand, 1986:26). Although these initiatives require several changes in the logistic support system, by reallocating support resources in response to changes in projected force needs logistics decision makers should be able to mitigate the effects of unexpected demands (Rand, 1984:3).

What changes are needed to provide more flexible support? Two promising options include expanding lateral resupply and lateral repair among theater locations. Also, closer coupling of depot repair to operational forces significantly increases aircraft availability (Rand, 1986:26). However, these changes would require new policies that integrate the logistics support system and the combat forces.

The Rand Corporation has developed a model called DRIVE (Distribution and Repair in Variable Environments), which will facilitate the integration of the logistic support system and the combat forces. DRIVE prioritizes depot repair and distribution of the repaired components based on the current worldwide asset position and flying requirements. Its purpose is to ensure that the repair and distribution of recoverable components yields the best support available. DRIVE accomplishes this by sequencing repair and distribution of assets to maximize the probability of achieving aircraft

availability goals given the expected flying requirements. DRIVE also considers the priority of each weapon system in terms of each unit's aircraft availability goal. It then determines specific depot repair priorities considering available repair resources (CLOUT Plans and Programs, 1987).

The DRIVE algorithm uses an four-quarter moving average to determine the expected demands at each base. The moving average is based on the worldwide average of base demands. The worldwide demand rate per 1000 flying hours is multiplied by the number of flying hours projected at each base to determine each base's demands. Each base's demands are based on the assumption that demand varies linearly with the number of flying hours. DRIVE uses this demand rate as the expected rate at each base and then computes a variance to mean ratio (Sherbrooke A/B formulation) to predict demand variability. The total demands and the variance to mean ratio are used to develop a negative binomial probability distribution at each base. DRIVE uses the demand distribution and the current asset position to compute the probability that a base will meet its availability goal. DRIVE then determines the increase in availability expected by adding a serviceable asset at a given base. It is through these calculations that DRIVE determines how many assets to repair and where the assets should be sent to get the greatest increase in aircraft availability (CLOUT Plans and Programs, 1987).

DRIVE prioritizes repair using a marginal analysis technique; it looks for the highest increase in availability for the hours needed to repair the unit. The increase in availabilty is divided by the total standard repair hours to determine the benefit to cost ratio. DRIVE continues to select the item that provides the highest payoff until all of the available goals are met, all possible repairs are performed, or it meets a given repair constraint. Until the development of the DRIVE model, there was no way to directly tie the impact of specific logistics actions to aircraft availability. DRIVE allows managers at all levels to prioritize support actions to provide the greatest increase in aircraft availability with available resources (CLOUT Plans and Programs, 1987).

Research Objective

It is important to understand how DRIVE forecasts demand rates in order to prioritize repair and distribution. We also need to know if the repair and distribution priorities dramatically change with the varying demand rates found throughout the Air Force.

The objective of this research is to determine the effect on DRIVE's repair priorities of using actual base demand rates to predict base demand instead of an average of worldwide demand rates. The individual base demand rates should produce a more accurate forecast for each base than a

forecast based on a worldwide average of every base's demand. More accurate forecasts can help to improve logistics support to weapon systems and better relate weapon system expenditures to combat capability. Further research could identify other actions that may improve DRIVE's performance such as adjusting excessive demand variability due to random occurrences.

Research Questions

In order to improve our understanding of demand variations and their effect on DRIVE's repair and distribution priorities this research will investigate the following questions.

1. How sensitive is DRIVE to varying demand rates?
2. How does using base specific demand rates affect DRIVE's repair priorities?

Limitations

This research was unable to determine the effect on aircraft availability of using base specific demand rates in the DRIVE model because no wartime demand rates for the F-16A bases in the DRIVE data base are known. If one of these bases were to deploy for 30 days under a wartime scenario, as in a Coronet Warrior exercise, their wartime demand rates would be available and the effect on aircraft availability could be determined.

This research was also unable to determine if using base specific demand rates in DRIVE more accurately predicted base demands than DRIVE's worldwide demand rates, because AFLC does not maintain a history of actual base demand data.

Overview

The following chapter investigates demand prediction techniques since DRIVE uses each base's predicted demand distribution to prioritize repair and allocate spares. A variety of forecasting methods will be reviewed along with recent research which analyzes the different methods.

Chapter III presents the methodology used to determine the effect of demand variations on DRIVE's repair priorities. Chapter IV analyzes the results of the study and Chapter V presents the conclusions of the research. Suggested areas of further research are also presented.

II. Literature Review

Introduction

The purpose of this literature review is to investigate different methods of forecasting item demand that could be used in the DRIVE model instead of its current four-quarter moving average of worldwide demands. An application of a Bayesian method, a moving average, and several exponential smoothing techniques will be presented. Then studies of demand prediction techniques will be reviewed. The literature review will aid in the selection of an appropriate forecasting technique to be used in this research.

Bayesian Inference

Zellner distinguishes the Bayesian approach to inference from other approaches because it uses numerical probabilities to represent degrees of confidence that we have in propositions about empirical phenomena rather than a probability frequency (Zellner, 1971:9-10). He continues:

> The degree of reasonable belief that we have in a proposition . . . depends on the state of our current information . . .. Therefore, in general a probability representing a degree of reasonable belief that we have in a proposition is always a conditional probability, conditional on our present state of information. As our information relating to a particular proposition changes, we revise its probability or our belief in it. This process of revising probabilities associated with

propositions in the face of new information is the essence of learning from expereience (Zellner, 1971:9-10).

Bayes theorem combines a prior probability associated with a particular proposition (based on our initial information, from previous data and studies, theoretical considerations, and casual observation) and a probability density function (the likelihood function) to arrive at the posterior probability (Zellner, 1971:10). The posterior probability depends on both the prior information and the new sample information. Bayes theorem is used to revise our initial prior probability to reflect the information in our new data.

The posterior probability density function can be used to make probability statements about a parameter; for example, to compute the probability that the parameter lies between two specific values. As more sample information becomes known, it will have greater influence on the posterior probability density function which, in turn, will become more concentrated about the true value of the parameter (Zellner, 1971:11).

Feeney and Sherbrooke, in their 1964 study, document an application of the Bayesian technique whereby an item's observed demand is compared to other items in the system to improve upon the knowledge about the item. The Bayesian approach makes possible the estimation of the probability that the item's mean demand is at various levels of demand instead of trying to give a point estimate of the item's true mean

demand. The probabilities are then used to analyze the risks and potential payoffs for maintaining various stock levels (Feeney and Sherbrooke, 1965:v).

Moving Average

The moving average technique averages the actual demand for the last _n_ time periods to derive the next period's forecast. The number of time periods to include in the forecast should be large enough to cancel random fluctuations but few enough so that irrelevant data from the past is discarded. It is called a moving average because the average changes over time with the addition of new data and the deletion of old data. As recent data becomes available for each time period, it is included in the forecast and the oldest data is excluded from the forecast. The following equation is a mathematical representation of a moving average:

$$\hat{Y}_t = (Y_{t-1} + Y_{t-2} + \ldots + Y_{t-n}) = \sum_{i=1}^{n} Y_{t-i}/n \qquad (1)$$

where

$\hat{Y}_t$ = forecast demand for period t,
Y_{t-i} = actual demand in period t - i,
n = number of time periods included in moving average

The number of time periods to use in the average is purely subjective, depending on the particular situation, and should be determined by experimentation. If too few time periods are used, the moving average forecast values fluctuate more than they probably should with only random variations in demand. When too many time periods are used, the moving average is too stable and fails to detect current trends. In general, moving averages dampen random demand variations and respond to trends with a delay (Tersine, 1988:46).

Exponential Smoothing

Exponential *Smoothing* is a type of moving average where past data are not given equal weight. Recent data is weighted more heavily than older data. The magnitude of the smoothing constant determines the level of weight assigned to recent data. The smoothing constant (a) lies between zero and one, where small values of a smooth recent trends and large values of a emphasize recent demand conditions (Tersine, 1988:53).

A major advantage of exponential smoothing is that it does not require the user to keep a long history of data. Only the previous forecast needs to be retained to include the effect of all past data. The simplest exponential smoothing technique estimates the magnitude of the data and filters out random demand variations. It predicts demand for

the next period by adding the previous forecast to a fraction of the difference between the actual demand from the last period and its forecast demand.

Current forecast level

= (previous forecast) + a(previous actual - previous forecast)

= a(previous actual) + (1-a)(previous forecast),

$$= aY_{t-1} + (1 - a)\hat{Y}_{t-1}, \qquad (2)$$

where the previous actual demand is labeled Y_{t-1}, and $\hat{Y}_{t-1}$ is the previous forecast (Tersine, 1988:53).

Comparison of Forecasting Techniques

In 1984, Sherbrooke analyzed worldwide base level demands from a sample of 1030 recoverable items over 16 quarters. Also included in this study were F-16 data on 810 recoverable items at two bases from the Abell, *et al*., study in 1982. The demands were by item during five six-month periods.

Sherbrooke found that demand in adjoining time periods was not independent; many items had mean demands that were not constant. He reported that a model that agrees with the data he analyzed must not assume demand in different periods is independent. The correlation between demands in two different time periods decreased as the time interval between the periods increased. He concluded that exponential

smoothing was a better predictor of mean demand than a moving average. Because of time-varying means, exponential smoothing with a constant of .4 on quarterly data reduced squared error 39 percent and reduced average absolute error 12 percent. The exponential smoothing forecasts were better than an eight-quarter moving average for all of the future time periods tested, from one to eight quarters away (Sherbrooke, 1984:23).

In 1987, the Logistics Management Institute completed one of the most comprehensive demand prediction studies undertaken for the Air Force in recent years. The objectives of this study were to see if the recommendations from Sherbrooke's 1984 study for predicting demand were consistent across weapon systems, and to use a more meaningful measure than squared error and average absolute error. Also, this study evaluated the forecasting methods on end item availability since availability is the Air Force's objective in allocating funds to spare parts.

The experiment consisted of 17 demand prediction techniques which fall into four categories: Bayesian, moving average, exponential smoothing, and second-order exponential smoothing. The second-order exponential smoothing was called "Holt linear estimation" which is described in Makridakis and Hibon (1979). It is an exponential smoothing method similar to that described earlier but it includes a second parameter to estimate any trend in the data. In this

study, Sherbrooke set the first parameter, alpha, at 0.4 and the second parameter, beta, at 0.5, after some trial and error.

The recommendations from the 1984 study did appear to hold consistently across the C-5, A-10, and F-16 weapon systems as represented in 16 quarters of world-wide demand data. Two of the major conclusions were:

1. Demand prediction techniques should allocate more weight to more recent data, because mean demand rates change over time.

2. Exponential smoothing is consistently the best technique of those tested for estimating mean demand. With quarterly data, a smoothing constant of about .4 appears best (Sherbrooke, 1987:17).

Sherbrooke also reports "less definitive" findings (they may depend on the techniques used in the study). Two of the findings are:

1. Bayesian techniques used in this study were good but not the best. The achieved availabilities were fairly high in most cases, but the predicted availabilities were almost always too high.

2. A different exponential smoothing constant for low-demand items did not improve predictions. There had been some suspicion that a lower exponential smoothing constant, equivalent to a longer history period, might improve predictions for very low-demand items (Sherbrooke, 1987:18).

The most significant conclusion of these studies that applies to this research is that demand in different periods is not independent - mean demand rates change over time. The correlation between demands in two different time periods decreased as the time interval between the periods increased. This implies a forecasting method that gives more weight to

recent data (i.e. exponential smoothing) should provide a better estimate of demand than a moving average which gives equal weight to the number of time periods included in the demand prediction.

The table below shows how exponential smoothing constants affect the weight given to the demands of previous periods (Tersine, 1988:55). A low smoothing constant allocates weight more evenly and smooths recent trend, whereas a large smoothing constant gives recent values more weight. When $\underline{a}$ = 0.1, the three recent periods account for only 0.1 + 0.09 + 0.081 = 0.271 or 27.1 percent of the predicted value. However, when $\underline{a}$ = 0.4, the three recent periods account for 0.4 + 0.24 + 0.144 = .784 or 78.4 percent of the forecast.

TABLE 1

Exponential Smoothing Constants

Exponential Smoothing Constant $\underline{a}$	Period Weight			
	k=1 $\underline{a}$	k=2 $\underline{a}(1-\underline{a})$	k=3 $\underline{a}(1-\underline{a})$	k=4 $\underline{a}(1-\underline{a})$
0	0	0	0	0
0.1	0.1	.09	.081	.0729
0.2	0.2	.16	.128	.1024
0.3	0.3	.21	.147	.1029
0.4	0.4	.24	.144	.0864
0.5	0.5	.25	.125	.0625
0.6	0.6	.24	.096	.0384
0.7	0.7	.21	.063	.0189
0.8	0.8	.16	.032	.0064
0.9	0.9	.09	.009	.0009
1.0	1.0	0	0	0

The number of time periods included in a moving average also affects the allocation of weight to recent data. In fact, there is a relationship between the moving average method and simple exponential smoothing. The stability of a moving average increases as the number of time periods in the moving average increases, while the stability of exponentially smoothed forecasts increases as $\underline{a}$ decreases. If $\underline{a}$ is the exponential smoothing constant, the corresponding number of periods in the moving average is (Tersine, 1988:56) :

$$n = (2 - \underline{a})/\underline{a} \tag{3}$$

Thus, a smoothed model with $\underline{a} = 0.4$ includes the same number of periods as a moving average model with $n = 4$.

Another interesting finding is that a lower exponential smoothing constant (0.1 was used in the 1987 study) did not improve predictions. In his 1980 study, Patterson stated that different exponential smoothing constants for different groups of items may improve demand predictions. He suggested further research to consider grouping homogenous items on the basis of item activity (high, medium, and low volume) or item essentiality (Patterson, 1980:20). This approach seems appealing in that it is similar to the Bayesian method that compares an item's observed demand to other items in the system. It would seem prudent to use a lower smoothing constant for low volume items and a higher smoothing constant

for higher volume items if the low volume items have more stable demand patterns.

Another exponential smoothing technique that deserves further review is adaptive exponential smoothing. In his article "A Comparsion of Adaptive Forecasting Techniques," Whybark (1972a) compared four approaches to adaptive forecasting, each representing a different way of modifying exponential smoothing to adapt to changes in the demand pattern (Whybark, 1972a:13-26). The adaptive models devise means for providing low smoothing constants when demand is stable and high smoothing constants when demand is shifting. The approaches Whybark discussed used the performance of the models as the basis for determining whether to change the smoothing constant.

Whybark classified adaptive smoothing models along two dimensions: 1) the frequency of evaluation of the forecasting performance, and 2) how the smoothing constant is determined once the evaluation indicates it should be changed. Some models use a fixed value of the smoothing constant for a specified number of periods and then evaluate the performance of the model (periodic evaluation). The model's performance determines whether a different smoothing constant should be used for the next set of periods. Other models evaluate forecasting performance every period to see if the smoothing constant is appropriate (continuous evaluation).

The second dimension of the model classification is based upon how the smoothing constant is changed once the evaluation indicates it should be changed. Some models restrict the amount of change that can be made while other models leave the change unrestricted. This provides a total of four types of models along the two dimensions which are illustrated in Table 2 (Whybark, 1972a:15).

TABLE 2

Classification of Adaptive Smoothing Models

Smoothing Constant	Periodic Evaluation	Continuous Evaluation
Restricted	Roberts and Reed, 1969	Whybark, 1972
Unrestricted	Eilon and Elmaleh, 1970	Trigg and Leach, 1960

Whybark tested the four models in a simulated inventory system. A total of 400 periods were generated of which the first 200 were used to initialize the models, and the remaining 200 were used to compare the models. The pertinent conclusions resulting from this study were:

1. The addition of an adaptive mechanism to the smoothing model provided positive improvement in its performance. Adapting the smoothing constant reduced both the forecast error and total costs.

2. The continuous evaluation models exhibited slightly better performance than the periodic evaluation models on total costs and consistently better performance on error standard deviation.

3. Adaptive forecasting techniques warrant consideration in logistics systems where low cost, reliable, short-term forecasts are required (Whybark, 1972b:25).

In his 1985 review of exponential smoothing models, Everette Gardner discussed other studies of adaptive forecasts that have resulted in less optimistic conclusions (Gardner, 1985). He listed several modifications to the adaptive forecasts that have been suggested to provide more stability in the predictions. One proposed alternative to adaptive parameters is to manually refit the forecasting model at regular intervals, using only recent data to derive the parameter values (i.e., Eilon and Elmaleh, 1970). Another alternative is to refit the model immediately after one of the tracking signals indicates the need to do so (Buffa, 1975). With either strategy, the refitting can be done automatically if one is willing to specify a set of permissible smoothing constant values (Gardner, 1985:21). Gardner stated that Eilon and Elmaleh as well as Buffa recorded worthwhile improvements in accuracy compared to models fitted only once to the early part of the series.

In 1980, Gardner and Dannenbring tested the performance of nine exponential smoothing models using a simulated sample of 9000 time series. The time series were simulated with a variety of noise levels and characteristics (constant mean, trends, and turning points). The purpose of the study was to identify guidelines to aid in the selection of an appropriate

forecasting model under different circumstances. The researchers proposed the following conclusions:

1. Adaptive models tend to overreact to random fluctuations in the time series. The forecasts are unstable even when the mean demand is stable. This instability offsets the advantage adaptive models have in responding to sudden shifts in demand.

2. Nonadaptive, trend adjusted models perform well under a variety of circumstances. They can react as well as the adaptive models to sudden shifts in demand with an appropriate smoothing constant.

3. A smoothing constant between .01 and .10 is recommended when the mean is stable and there is no apparent trend. Higher values could be used to hedge against the development of trends, however, trend adjusted models perform well even if there is no trend in the series.

4. When there is a definite trend, Holt's model performs well with an alpha between .01 and .10 and a beta at .5 or .10 (Gardner and Dannenbring, 1980:382).

Although the more sophisticated prediction models may improve forecasting accuracy, no convincing advantage has been demonstrated as yet. In 1982, seven forecasting experts compared 24 time series methods for a sample of 1001 series (Makridakis et al., 1982). The purpose of the study was to evaluate major extrapolation methods and look at the different factors that affected forecasting accuracy. Most of the methods were automatic and therefore eliminated subjective adjustments from affecting the accuracy of the models. This study was important to forecasting users not just because it was very comprehensive, but because it indicated that the most accurate forecasting method varies depending on the forecasting situation. The results indicated that forecasting accuracy can be improved considerably by using different

methods depending on the type of data (yearly, quarterly, monthly), the type of series (micro, macro, etc.), and the time horizon of forecasting. With monthly and micro data, deseasonalized single exponential smoothing performed very well; whereas, with yearly and quarterly data, it did not perform as well as other methods. The researchers concluded that simple models performed relatively well in comparison with statistically sophisticated models when there is considerable randomness in the data. The researchers suggested that the sophisticated methods may extrapolate too much trend and lead to overestimation, and this is the reason why simple models perform relatively well in comparison.

In addition to using different forecasting methods under different circumstances, managers need to consider the assumptions their forecasts are based upon. In 1988, the Air Force Logistics Management Center (AFLMC) investigated the assumption that demand varies linearly with flying hours. This is important to the Air Force because forecasts derived from worldwide demands assume that demand varies linearly with the number of flying hours. The DRIVE model makes this assumption in its forecasts and wartime requirements for each Air Force unit are determined by multiplying the worldwide demand rate per 1000 flying hours by the number of flying hours for each unit. The researchers used a sample of 176 items consumed at the following units: Little Rock (76 aircraft), Pope (48 aircraft), Clark (16 aircraft), and

Little Rock ANG (6 aircraft). The results of the study indicated that demand does not vary linearly with the number of aircraft a base possesses.

The researchers also took a random sample of 30 items consumed by the following units: Clark (16 aircraft), McCord (16 aircraft), Van Nuys (16 aircraft), and Willow Grove (9 aircraft). Next, the researchers took a random sample of 34 items consumed by the following units: Dobbins (24 aircraft), New Orleans (21 aircraft), Minot (18 aircraft), and McCord (16 aircraft). The study revealed that the linear relationship between demand and the number of aircraft possessed was stronger for similar sized units (AFLMC, 1988). This research supports other studies that indicate there is little evidence to support the assumption of linearity (Hodges, 1985 and Lockette, 1984).

Summary

This literature review has investigated different methods of forecasting item demand. A variety of studies comparing demand prediction techniques were presented, some of which identified refinements to basic forecasting methods. Depending on the research and the data used, different methods produced better results. The literature review revealed that an appropriate forecasting method for this research study should be robust due to the time varying means many Air Force items have and due to the uncertainties of

operating in a wartime environment. Since the DRIVE model will be used in wartime to produce short term repair and distribution priorities, the forecasting method should also produce accurate short term forecasts.

The literature review suggested that certain forecasting methods may be inappropriate for use in this research. The Bayesian forecasting method does not seem appropriate for Air Force data because many of the items have time-varying means. The posterior probability density function may not become more concentrated about the "true" value of the parameter because of the changing means. The literature review also suggested that adaptive forecasting methods tend to provide unstable forecasts.

Sherbrooke's studies recommended that the forecasting method should give recent data more weight because Air Force items have time-varying means. He concluded that exponential smoothing was a better predictor of mean demand than a moving average. Sherbrooke also concluded that with quarterly worldwide data, exponential smoothing with a constant of 0.4 appeared best. Although the 1982 reveiw of forecasting methods was not based on Air Force data, the researchers concluded that with monthly and micro data, deseasonalized single exponential smoothing performed very well. The researchers also concluded that simple models performed relatively well in comparison with statistically sophisticated models when there is considerable randomness in the data.

The AFLMC report indicated that demand does not vary linearly with the number of aircraft a base possesses. This suggests that wartime requirements should not be determined by multiplying a base's flying hours by the worldwide demand rate.

III. Methodology

Introduction

This chapter details the research methodology used to determine the effect of demand variations on DRIVE's repair priorities. Because there are high levels of demand variability from base to base, (Rand, 1982b) using a worldwide average of every base's demand does not give an accurate picture of each base's current demand patterns. Both the DRIVE model and the D041 use worldwide demand rates to determine expected demands at each base. However, these forecasts are based on the assumption that demand varies linearly with flying hours. The AFLMC study supported other studies that indicated that demand does not vary linearly with flying hours. Instead of a forecast based on a worldwide average of every base's demand, this study determined the effect of using each base's demand history to forecast its demand rate. By using each base's demands, we should get a more accurate estimate of its current demand patterns. Although the literature review suggested that exponential smoothing may provide a more accurate short term forecast, this study did not use exponential smoothing because AFLC does not maintain a history of actual base demand rates to generate an exponentially smoothed forecast. Therefore, an 18 month moving average of each base's demand was taken from the D028 Central Requirements Leveling data base to forecast base

demand. This chapter presents a summary of the DRIVE data base as well as the assumptions used in the DRIVE model and in this study.

DRIVE Data Base

The F-16 Avionics Item Managers at the Ogden Air Logistics Center (OO-ALC) have used the DRIVE model since October 1986 to prioritize depot repair and to allocate depot spares in order to fill existing base requisitions. This is in contrast with allocating spares according to the Uniform Military Movement and Issue Priority System (UMMIPS). The information in the DRIVE data base has been used by the Air Force Logistics Command to compare the aircraft availability rates resulting from DRIVE's repair priorities and distribution of depot spares with the aircraft availability rates resulting from the Uniform Military Movement and Issue Priority System. The aircraft availability rates derived from the DRIVE data base were based on demand forecasts from the DRIVE model which predicts demands at each base using a four-quarter moving average of worldwide demands.

The avionic equipment in the DRIVE data base is repaired with one of the four F-16 Avionic Intermediate System's test sets. The DRIVE data base includes 32 line replacement units (LRUs), 233 shop replacement units (SRUs), and 21 F-16 bases. The bases are listed in Appendix A and the LRUs are listed in Appendix B. Air Force wide, LRUs and SRUs accounted

for approximately 54 percent or 2 billion dollars of the 1987 Depot Programmed Equipment Maintenance (DPEM) budget (Air Force Logistics Command, 1987).

Twelve of the 21 bases in the DRIVE data base are combat coded and therefore have wartime flying hour commitments in addition to peacetime flying hours. Although the bases and their missions are diverse, the DRIVE model uses common assumptions across all operating locations.

Assumptions

The prototype implementation of DRIVE includes the following assumptions:

1. Expected demand for an item and a variance to mean ratio form a negative binomial probability distribution which is used to determine the probability of demands on the depot.
2. At base level, cannibalizations are done whenever possible for LRUs and SRUs to consolidate shortages on the fewest number of aircraft.
3. There is no base repair of SRUs.
4. Every LRU repaired at base level requires SRUs to be replaced.
5. Standard repair hours for LRUs and SRUs are valid measures of resource consumption for individual repair actions.
6. Units with a common Stock Record Account Number (SRAN) can share assets (CLOUT Plans and Programs, 1987).

Research Methods

The objective of this study was to determine the effects of demand variations on DRIVE's repair priorities. Two different base demand forecasting methods were used in the

DRIVE model to forecast quarterly base demands. The different forecasting methods were DRIVE's four-quarter moving average forecast of <u>worldwide</u> base demands, and an 18 month moving average forecast of <u>each base's</u> demand. The 18 month moving average forecast of base demands is currently used in the Recoverable Central Leveling System (D028) to provide centrally computed stock levels to Air Force users for selected repair cycle items.

The comparison of the forecasting methods was accomplished by using DRIVE's current forecasting method to predict base demands and then by changing the DRIVE algorithm to forecast demand by using an 18 month moving average forecast of each base's demand. The DRIVE model was used to forecast quarterly demands at each base for the third and fourth quarters of 1987. DRIVE used these predicted demands to produce a list of items for depot repair during the quarter given the number of repair hours available. The number of LRU repair hours available during 1987 was 14,000; however, recent budget restrictions reduced the amount of repair available to 10,000 hours. This study used LRU repair constraints of 1,000 through 15,000 hours at 1,000 hour intervals to observe how the repair lists changed given the different quarterly repair hour constraints. A repair list with no repair constraint was also used to see the optimal number of LRUs and SRUs that DRIVE recommended for repair during the quarter. These quarterly repair lists DRIVE

produced from the two forecasting methods were used to determine the effect of demand variations on DRIVE's repair priorities.

The different forecasting methods were evaluated using a paired difference t statistic. The quarterly LRU repair quantities for the forecasting methods were paired and the differences were analyzed. The paired difference t-test determined if the quarterly repair quantities for the forecasting methods were significantly different using an alpha of 0.05. This implies that only five percent of the time would the null hypothesis, stating the repair quantities are equal, be rejected when it should not have been rejected. In addition to the t-test, graphs of DRIVE's recommended repair quantities per repair hour for the four critical F-16A LRUs and their SRUs were used to evaluate the forecasting methods. The DRIVE model has consistently identified these four LRUs as critical items since August 1987. The graphs show how the number of LRUs and SRUs to repair changes given different repair constraints.

Summary

This chapter has given an overview of the DRIVE data base and has detailed the assumptions made in the DRIVE model. This research compared the priority lists DRIVE produced from the two different base demand forecasting

methods to see how sensitive DRIVE is to demand variations. The quarterly LRU repair quantities were evaluated using the paired t statistic to determine if the forecasting methods produced different repair quantities. Graphs of the repair quantities DRIVE recommended per depot repair hour for the four critical F-16A LRUs and their SRUs were also used to evaluate the forecasting methods. The graphs indicate how the number of LRUs and SRUs to repair change given different repair constraints. This chapter outlined the research methods used in this study to provide a background for the next chapter's analysis.

IV. Analysis

Introduction

This chapter analyzes the effects of demand variations on DRIVE's repair priorities by comparing the quarterly repair lists DRIVE produced from the two different base demand forecasting methods. Graphs of the repair quantities DRIVE recommended per depot repair hour for the four critical F-16A LRUs and their SRUs were also used to evaluate the forecasting methods.

Results

Table 3 lists the number of LRUs DRIVE recommended for repair for each of the four F-16 avionics test stands for the third and fourth quarters of 1987. The repair lists were based on the current amount of depot repair available, 10,000 hours. The differences between the four-quarter moving average of worldwide demands (D041) and the 18 month moving average of base specific demands (D028) were analyzed using the paired t statistic which is explained in Appendix C. The t-test revealed that at an alpha of 0.05 the null hypothesis, stating the repair quantities are equal, should be rejected. The two forecasting methods produced significantly different repair priorities for both the third and fourth quarters of

1987. The differences in the repair lists are solely due to the different demand rates the two forecasting methods provide.

TABLE 3.
LRU Repairs by Shop

NSN	Description	Sep D041 Quan	Sep D028 Quan	Dec D028 Quan	Dec D041 Quan
COMPUTER INERTIAL STAND					
1270-01-045-3976WF	FIRE COMP	2	21	55	1
6605-01-046-3533WF	FC NAV PAN	91	98	73	102
6605-01-087-6645WF	INU 74DA0	102	74	74	78
6610-01-039-7817WF	ACCELER AS	2	4	0	1
6610-01-123-0046WF	ECA 14FB0	6	0	0	12
6615-01-042-7834WF	GYRO	6	61	66	8
6615-01-127-3160WF	PANEL	7	17	12	1
6615-01-129-7445WF	PANEL TRIM	18	36	55	31
6615-01-161-1592WF	FLT CTL CO	4	5	4	3
6615-01-172-0136WF	FLCC	11	6	1	12
DISPLAY STAND					
1270-01-094-6872WF	RCP 74AH0	6	74	74	11
1270-01-122-9955WF	HUD ELECT	0	11	20	3
5841-01-096-3945WF	DISP 74EA0	12	74	74	17
5841-01-096-4833WF	RDR E74EB0	5	74	74	14
PNEUMATICS and PROCESSORS STAND					
1270-01-133-6494WF	DIG SIG PR	1	18	24	6
1270-01-209-9982WF	COMPUTER 7	4	7	7	4
1280-01-080-0203WF	CRIU 75DE0	13	75	75	16
1280-01-109-1499WF	MRIU 75DB	34	75	75	25
1280-01-121-6879WF	PANEL STOR	16	2	2	18
1280-01-240-8595WF	CIU	8	17	4	12
5999-01-080-3978WF	JRIU 75DD0	10	75	75	10
6610-01-089-1018WF	COMPUTR CA	3	13	31	19
6615-01-042-7835WF	PNE SENSOR	1	0	0	1
RADIO FREQUENCY STAND					
1270-01-093-2174WF	ANTENNA RA	42	0	0	66
1270-01-093-2256WF	RADAR XMTR	14	48	37	17
1270-01-102-2962WF	LOW PWR RF	15	12	9	28
1270-01-102-2963WF	LOW PWR RF	15	9	9	19
1270-01-102-2965WF	LOW PWR RF	28	9	9	41
1270-01-102-2966WF	LOW PWR RF	15	13	12	19
1270-01-146-4630WF	ANTENNA	1	0	0	1

Table 4 shows the difference in the repair quantities and the absolute value of the repair differences for the July through September, and October through December 1987 quarters.

TABLE 4.
Comparison of LRU Repairs

Sep D028 Quan	Sep D041 Quan	Diff	Dec D028 Quan	Dec D041 Quan	Diff
21	2	19	55	1	54
98	91	7	73	102	-29
74	102	-28	74	78	-4
4	2	2	0	1	-1
0	6	-6	0	12	-12
61	6	55	66	8	58
17	7	10	12	1	11
36	18	18	55	31	24
5	4	1	4	3	1
6	11	-5	1	12	-11
74	6	68	74	11	63
11	0	11	20	3	17
74	12	62	74	17	57
74	5	69	74	14	60
18	1	17	24	6	18
7	4	3	7	4	3
75	13	62	75	16	59
75	34	41	75	25	50
2	16	-14	2	18	-16
17	8	9	4	12	-8
75	10	65	75	10	65
13	3	10	31	19	12
0	1	-1	0	1	-1
0	42	-42	0	66	-66
48	14	34	37	17	20
12	15	-3	9	28	-19
9	15	-6	9	19	-10
9	28	-19	9	41	-32
13	15	-2	12	19	-7
0	1	-1	0	1	-1
		436			355

Absolute Difference 789 Absolute Difference 690

For the July through September 1987 quarter, the D028 forecasts resulted in DRIVE recommending 436 fewer LRUs for

repair. For the October through December 1987 quarter, the D028 forecasts led DRIVE to recommend 355 fewer LRUs for repair. DRIVE did not recommend repairing less quantities of all the LRUs. For the July through September quarter, the absolute value of the differences was 690, and for the October through December quarter, the absolute value of the differences was 789. The two different forecasting methods changed the repair priorities for each of the 32 avionic LRUs. Unfortunately, the impact on aircraft availability of these changes could not be determined since none of the wartime demand rates for these bases are known. It could also not be determined which forecasting method was more accurate because AFLC does not maintain a history of actual base demand rates. However, we should achieve a more accurate picture of each base's demand patterns by using each base's demand rates instead of an average of every base's demands, since demand varies significantly from base to base. Actual base demand rates need to be retained to accurately assess the impact on aircraft availability of using base demand rates. The D028 data used in this research appeared to be incomplete since some bases had no D028 demand history for some of the LRUs.

Table 5 lists the D028 demand rates of critical LRUs for the non combat coded F-16A bases. There are two quarters of D028 demand rates; each quarterly rate represents an 18 month moving average of each base's demand rate.

Table 5. D028 Demand Rates per 100 Flying Hours

September 1987 NSN	Base	Demand Rate	December 1987 NSN	Base	Demand Rate
1270011022962	FB2823	0.0187	1270011022962	FB2823	0.0188
1270011022962	FB4814	0.0942	1270011022962	FB4814	0.0918
1270011022962	FB4887	0.0293	1270011022962	FB4887	0.0572
1270011022962	FB6022	0.0167	1270011022962	FB6022	0.0159
1270011022962	FB6091	0.0333	1270011022962	FB6091	0.0443
1270011022962	FB6261	0.0055	1270011022962	FB6261	0.0222
1270011022963	FB2805	0.0080	1270011022963	FB2805	0.0112
1270011022963	FB2823	0.0285	1270011022963	FB2823	0.0296
1270011022963	FB4814	0.1308	1270011022963	FB4814	0.1351
1270011022963	FB4887	0.0205	1270011022963	FB4887	0.0217
1270011022963	FB6022	0.0369	1270011022963	FB6022	0.0425
1270011022963	FB6091	0.0307	1270011022963	FB6091	0.0286
1270011022963	FB6151	0.1050	1270011022963	FB6151	0.1050
1270011022963	FB6261	0.1090	1270011022963	FB6261	0.1202
1270011022965	FB2805	0.0134	1270011022965	FB2805	0.0135
1270011022965	FB2823	0.0405	1270011022965	FB2823	0.0576
1270011022965	FB4814	0.2068	1270011022965	FB4814	0.2081
1270011022965	FB4887	0.0997	1270011022965	FB4887	0.1226
1270011022965	FB6022	0.0186	1270011022965	FB6022	0.0224
1270011022965	FB6091	0.0060	1270011022965	FB6091	0.0222
1270011022965	FB6151	0.0450	1270011022965	FB6151	0.0450
1270011022965	FB6261	0.0553	1270011022965	FB6261	0.0259
1270011022966	FB2823	0.0129	1270011022966	FB2823	0.0109
1270011022966	FB4814	0.2225	1270011022966	FB4814	0.2324
1270011022966	FB4887	0.0352	1270011022966	FB4887	0.0326
1270011022966	FB6022	0.0068	1270011022966	FB6022	0.0091
1270011022966	FB6261	0.0055	1270011022966	FB6261	0.0277
6605010463533	FB2805	0.0052	6605010463533	FB2805	0.0052
6605010463533	FB2823	0.0361	6605010463533	FB2823	0.0434
6605010463533	FB4814	0.3315	6605010463533	FB4814	0.3297
6605010463533	FB4887	0.2251	6605010463533	FB4887	0.2042
6605010463533	FB6022	0.0554	6605010463533	FB6022	0.0505
6605010463533	FB6091	0.0241	6605010463533	FB6091	0.0480
6605010463533	FB6151	0.0670	6605010463533	FB6151	0.0781
6605010463533	FB6261	0.0927	6605010463533	FB6261	0.1046
6605010876645	FB2805	0.0426	6605010876645	FB2805	0.0426
6605010876645	FB2823	0.0727	6605010876645	FB2823	0.0531
6605010876645	FB4814	0.5659	6605010876645	FB4814	0.6107
6605010876645	FB4887	0.3136	6605010876645	FB4887	0.3433
6605010876645	FB6022	0.0837	6605010876645	FB6022	0.0984
6605010876645	FB6091	0.0908	6605010876645	FB6091	0.1319
6605010876645	FB6151	0.0585	6605010876645	FB6151	0.0807
6605010876645	FB6261	0.1020	6605010876645	FB6261	0.1681

There is considerable variation between bases for both the third and fourth quarters of 1987; however, the demand rate at a base remains relatively stable between the quarters. The D028 18 month moving average appears to dampen the actual base demand rates. The D028 demand rates reveal that some bases demands are more than ten times higher than other base's demands. These observations are consistent across all of the LRUs and SRUs at each of the 21 F-16 bases. Since the worldwide demand rates are an average of all of the base's demands, the requirements of the bases with unusually high demands are not met, while the bases with low demands can not justify the requirements that the worldwide demand rates set for them. By taking an average of the highly different base demand rates, the DRIVE model does not properly allocate requirements according to each base's demands.

DRIVE sequences the repair and distribution of assets to maximize the probablity of each base achieving its aircraft availability goals. Using worldwide demand rates to determine the expected demands at each base does not support the needs of each base according to its recent demand history. In peacetime, DRIVE may better support the needs of each base by using each base's demand history to forecast demands. During war, when the bases may operate in a totally different environment, an average of several bases' demands may be more appropriate.

Figures 1 through 16 illustrate graphs of the repair quantities resulting from the two forecasting methods for the four critical F-16A LRUs and their SRUs. The graphs show that for the third and fourth quarters of 1987, the D028 forecasts recommended fewer quantities of LRU repairs but not fewer SRU repairs across all of the critical SRUs. The D028 forecasts also required fewer repair hours to satisfy the optimal number of LRUs and SRUs DRIVE recommended for repair.

It is interesting to note that all of the LRU and SRU repair quantities, based on the D028 forecasts, could be satisfied with 14,000 repair hours, the number of hours available for depot repair in 1987. Many of the LRU and SRU repairs based on the D041 forecasts would not be met with 14,000 hours of repair. The D028 LRU and SRU repair quantities reach the predicted optimal number of repairs using less repair hours. This is most likely a result of incomplete D028 data; the bases with no D028 demands may have reduced the repair requirement beyond the level their actual demands would have recommended. Another possible explanation is that the unusually high demand rates for an item at one base may increase the worldwide requirements beyond the level predicted by each base's demands. Figures 1 through 16 also show that the repair quantities of LRUs and SRUs, based on the D041 demand rates, vary more than the D028 repair quantities from one quarter to the next. This occurs for three of the four critical LRUs and their SRUs. This indicates that the D028 18

month moving average forecasts are less variable than the four-quarter moving average forecast DRIVE uses. This reseach could not determine which forecast was more accurate because a history of the actual base demand rates was not maintained.

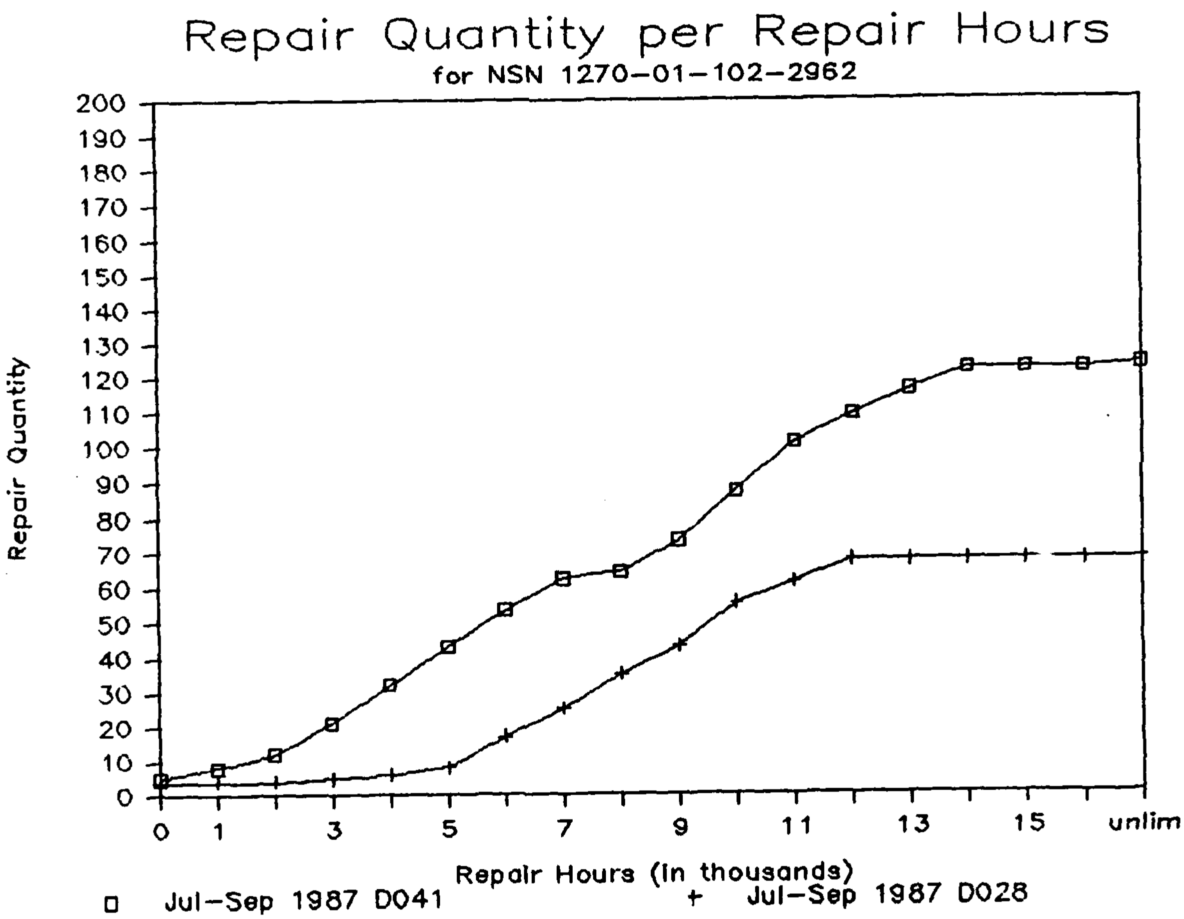

Figure 1. Jul - Sep 1987 Repair of LRU 1270-01-102-2962

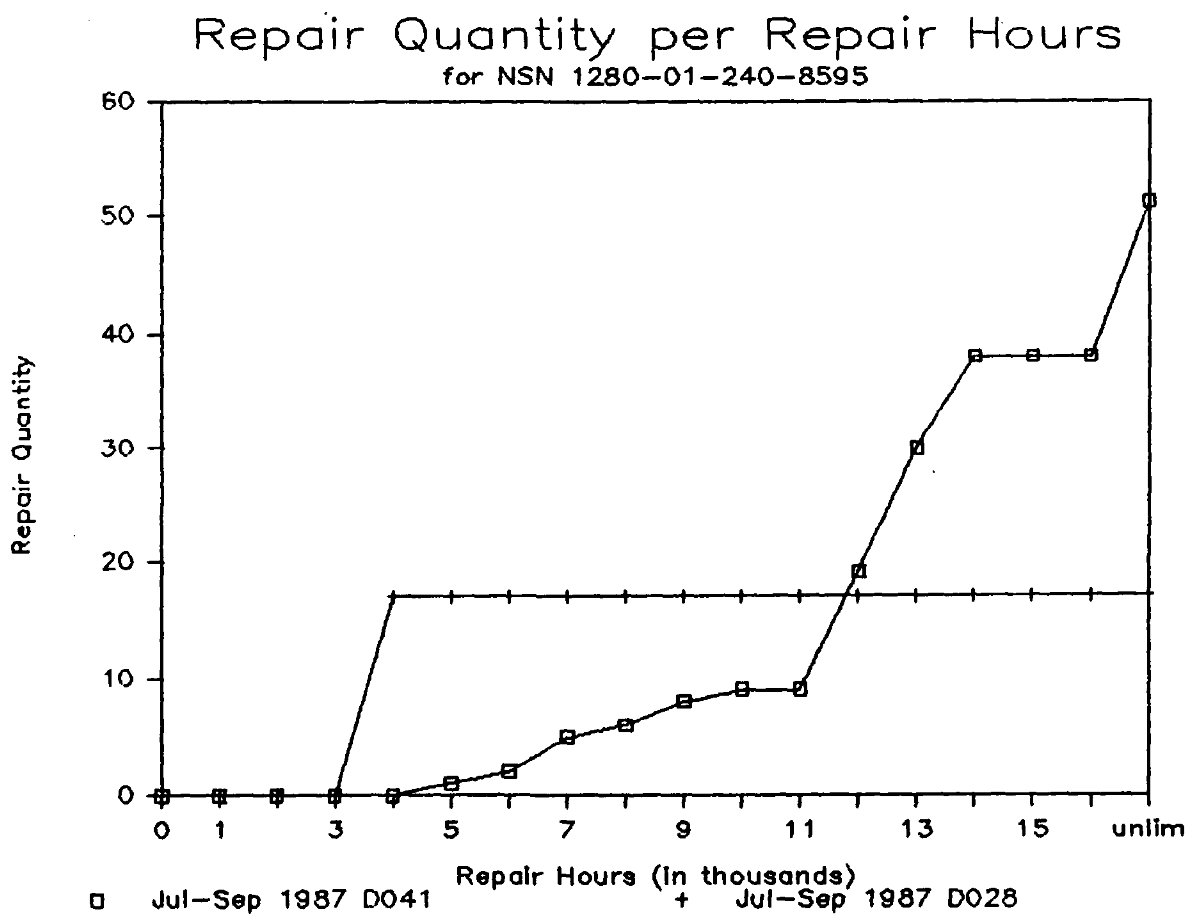

Figure 2. Jul - Sep 1987 Repair of LRU 1280-01-240-8595

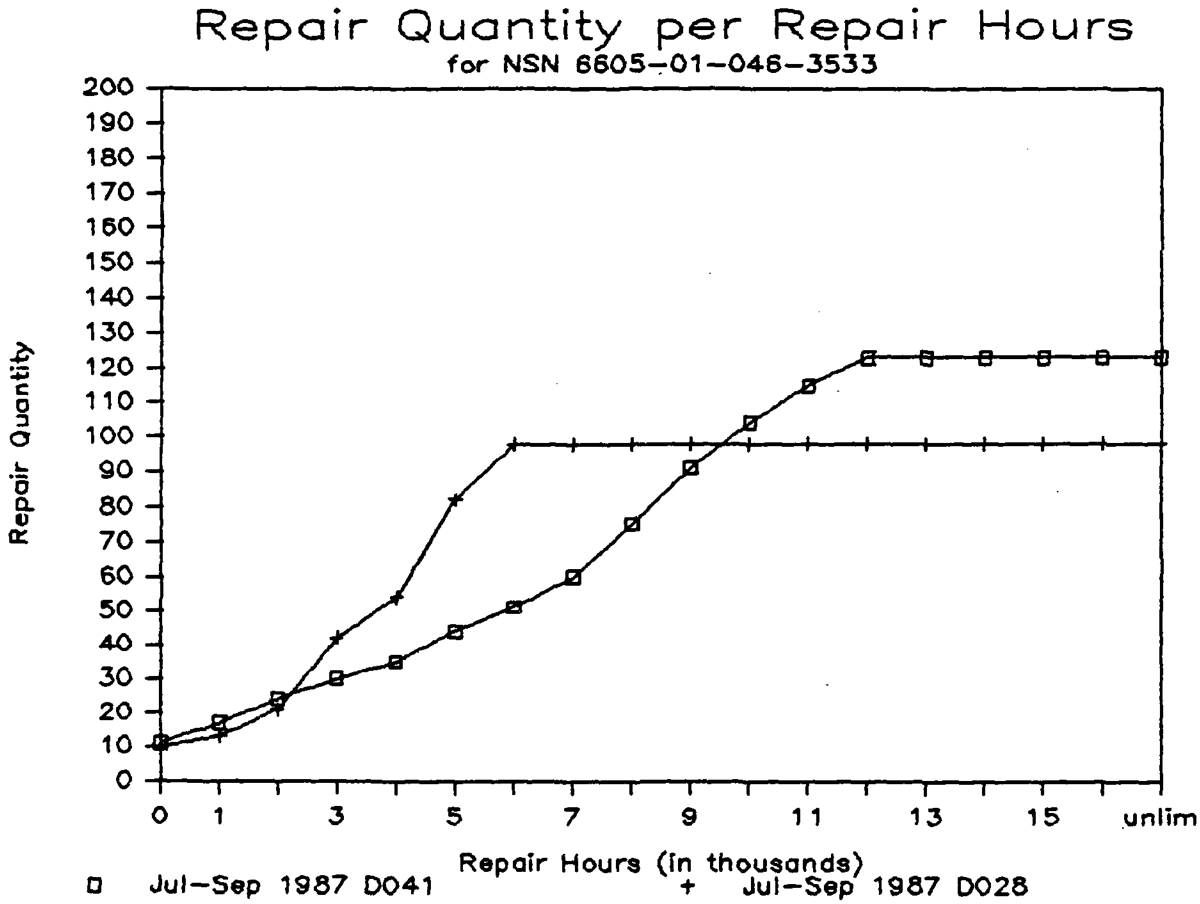

Figure 3. Jul - Sep 1987 Repair of LRU 6605-01-046-3533

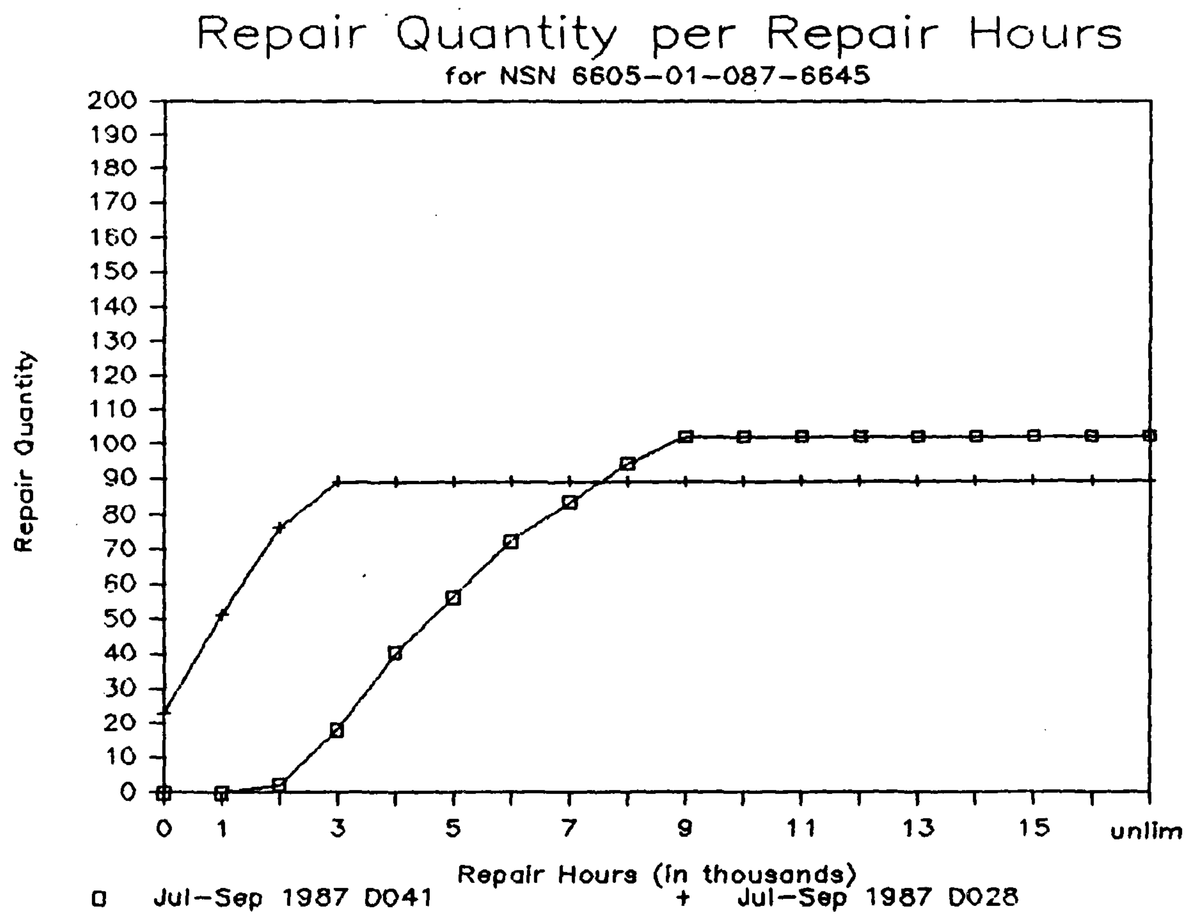

Figure 4. Jul - Sep 1987 Repair of LRU 6605-01-087-6645

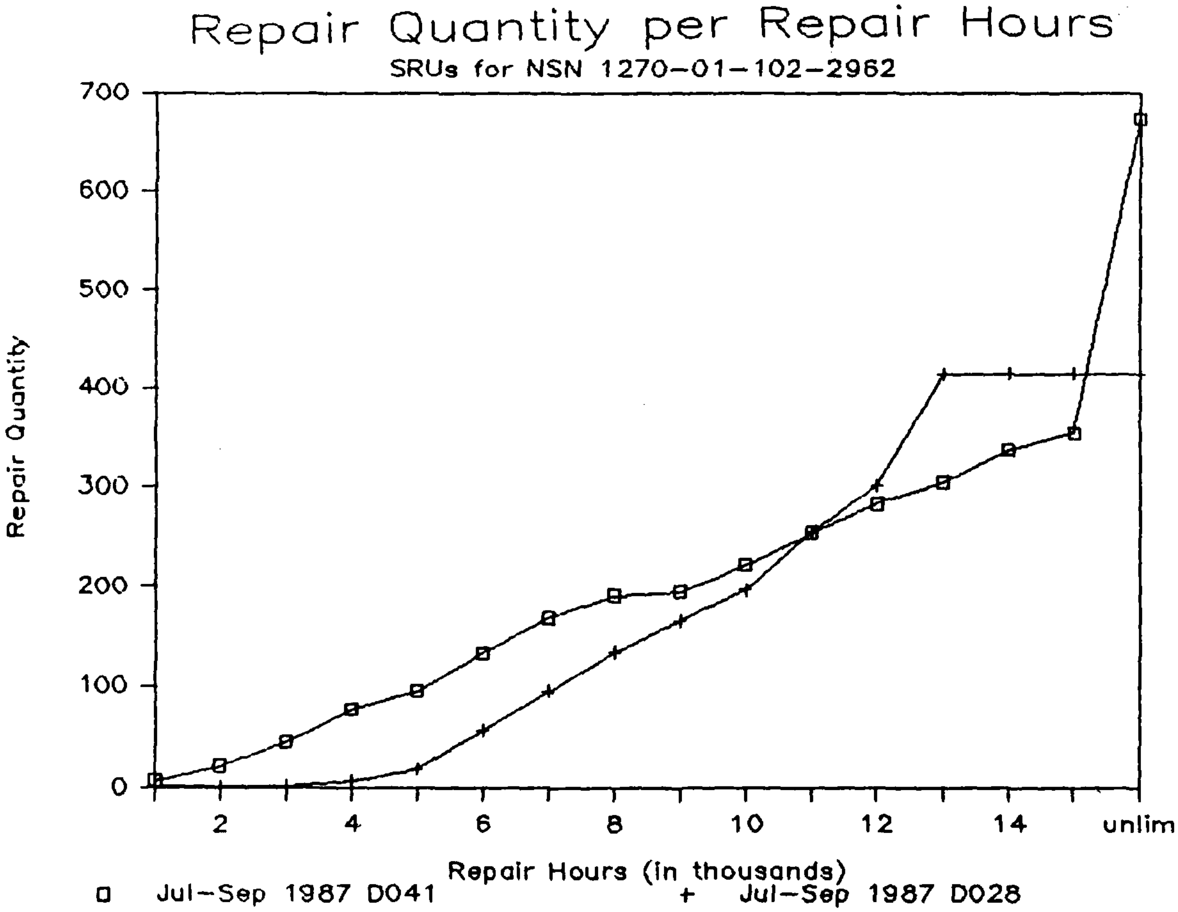

Figure 5. Jul - Sep 1987 SRU Repairs of 1270-01-102-2962

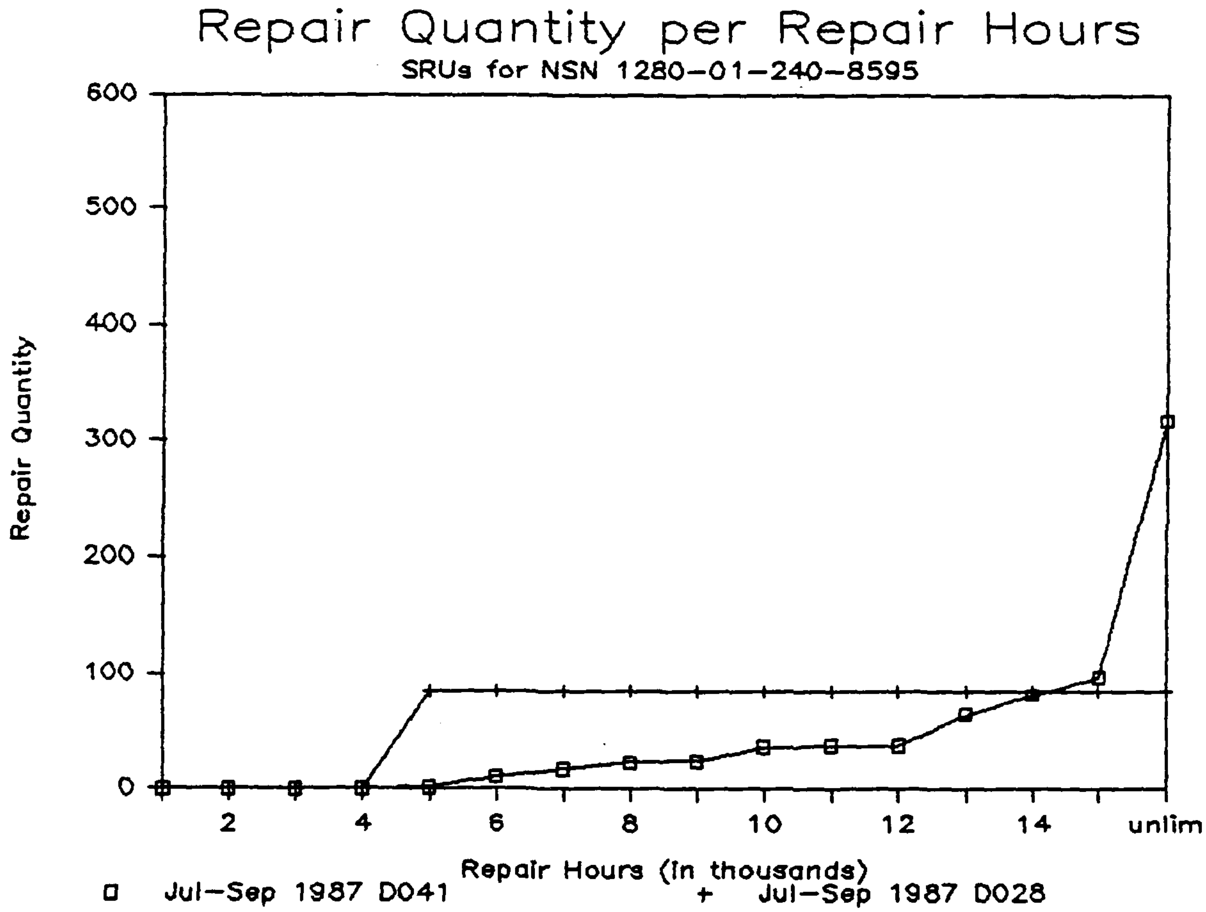

Figure 6. Jul - Sep 1987 SRU Repairs of 1280-01-240-8595

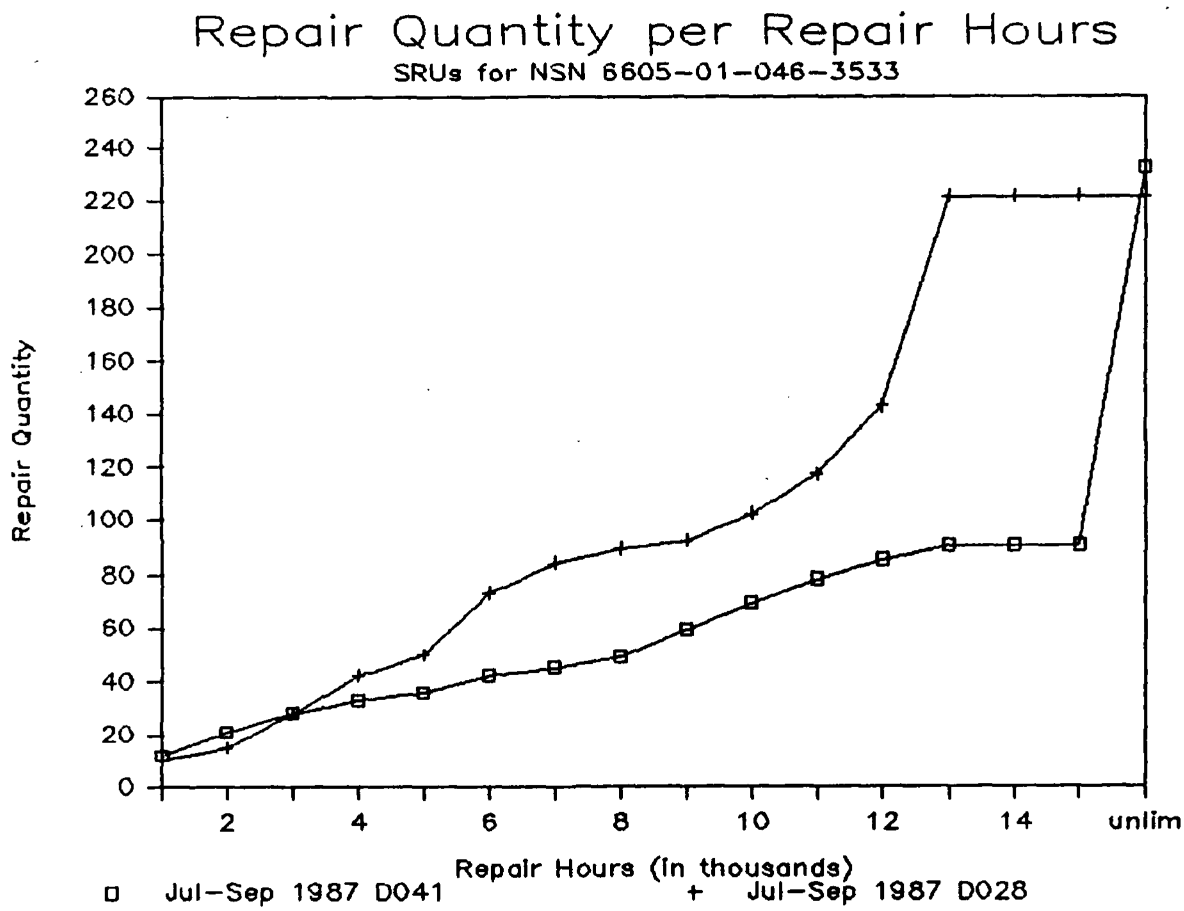

Figure 7. Jul - Sep 1987 SRU Repairs of 6605-01-046-3533

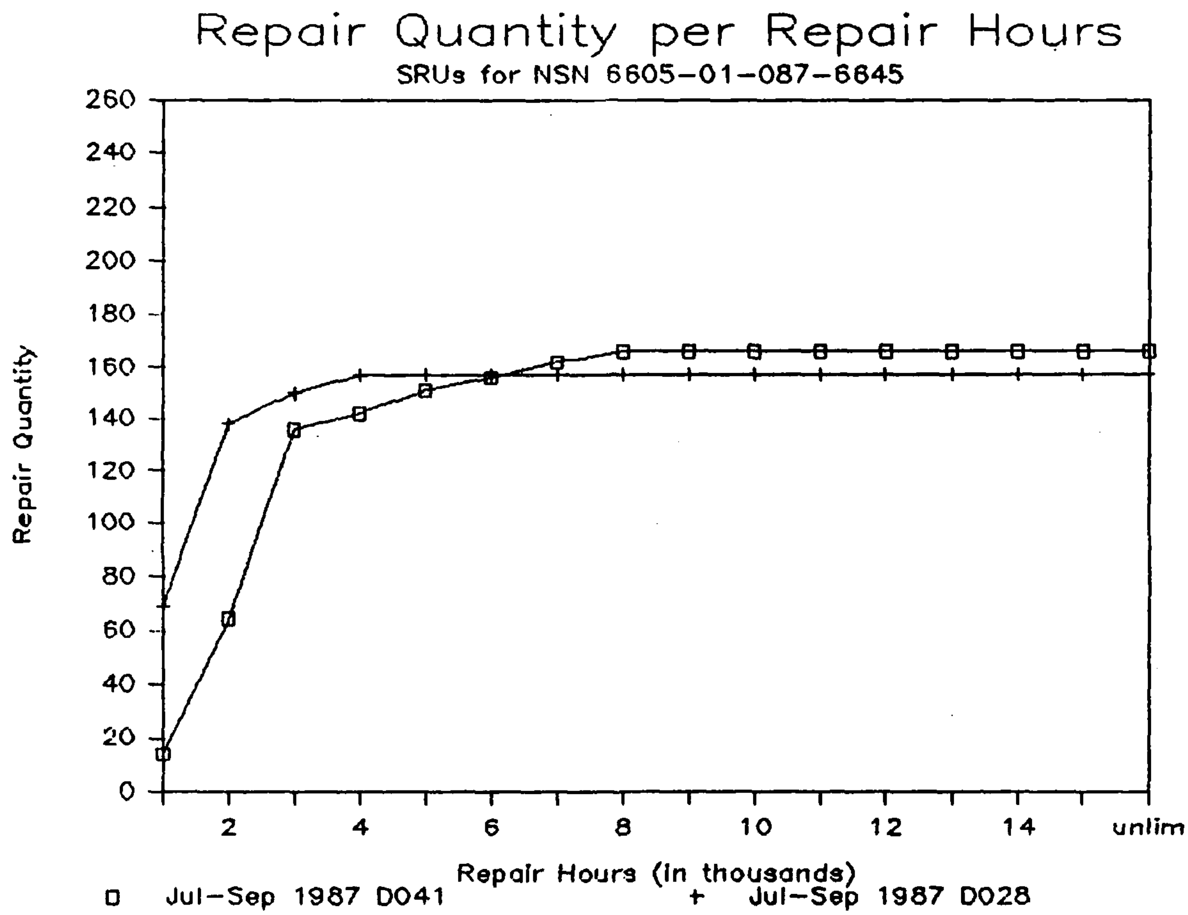

Figure 8. Jul - Sep 1987 SRU Repairs of 6605-01-087-6645

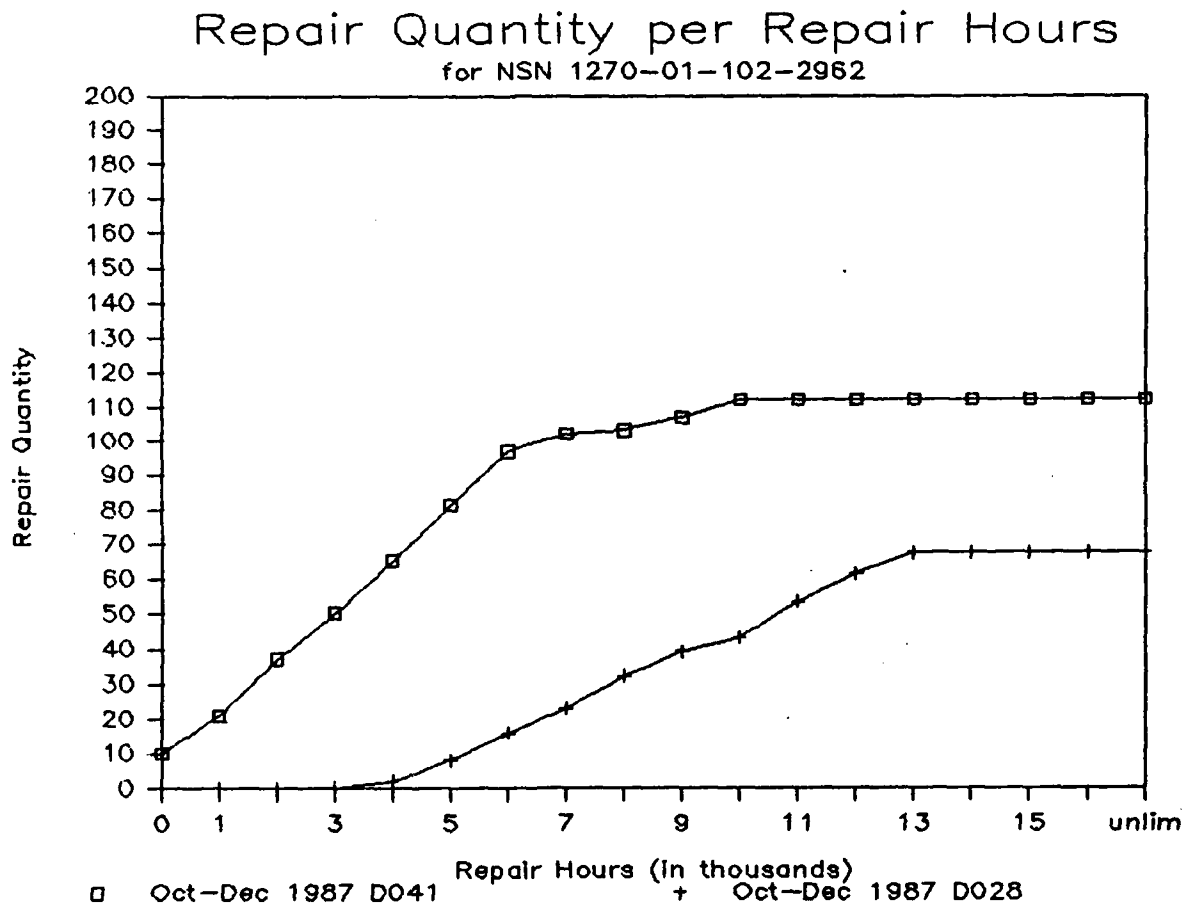

Figure 9. Oct - Dec 1987 Repair of LRU 1270-01-102-2962

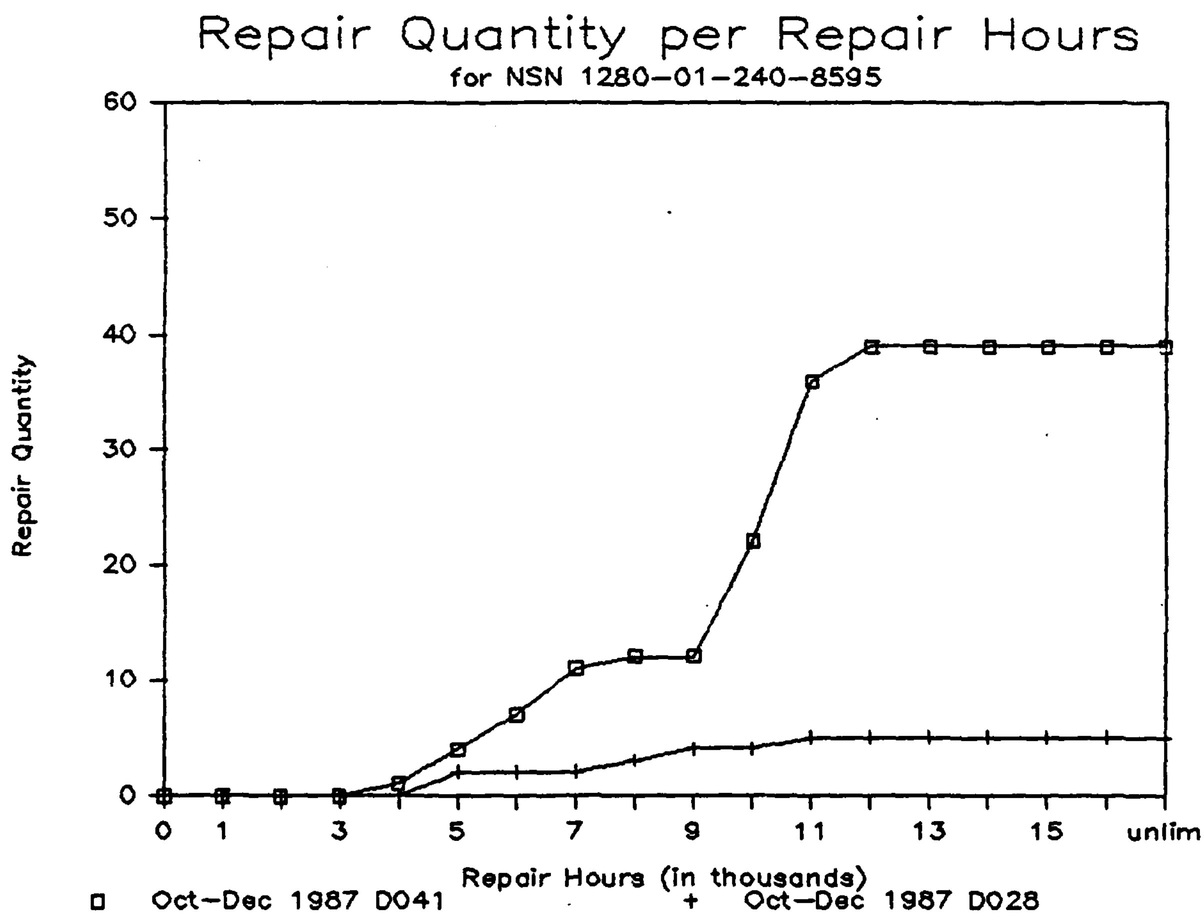

Figure 10. Oct - Dec 1987 Repair of LRU 1280-01-240-8595

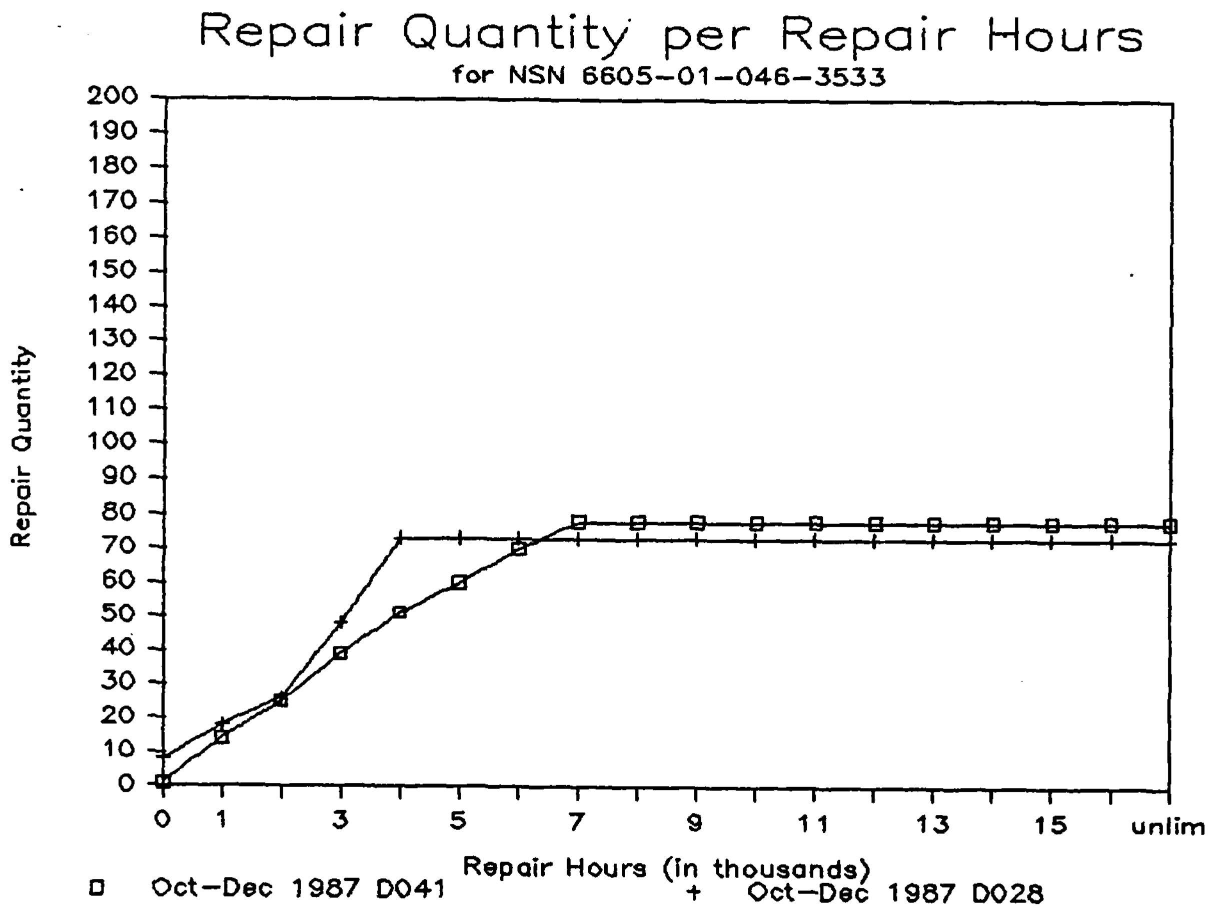

Figure 11. Oct - Dec 1987 Repair of LRU 6605-01-046-3533

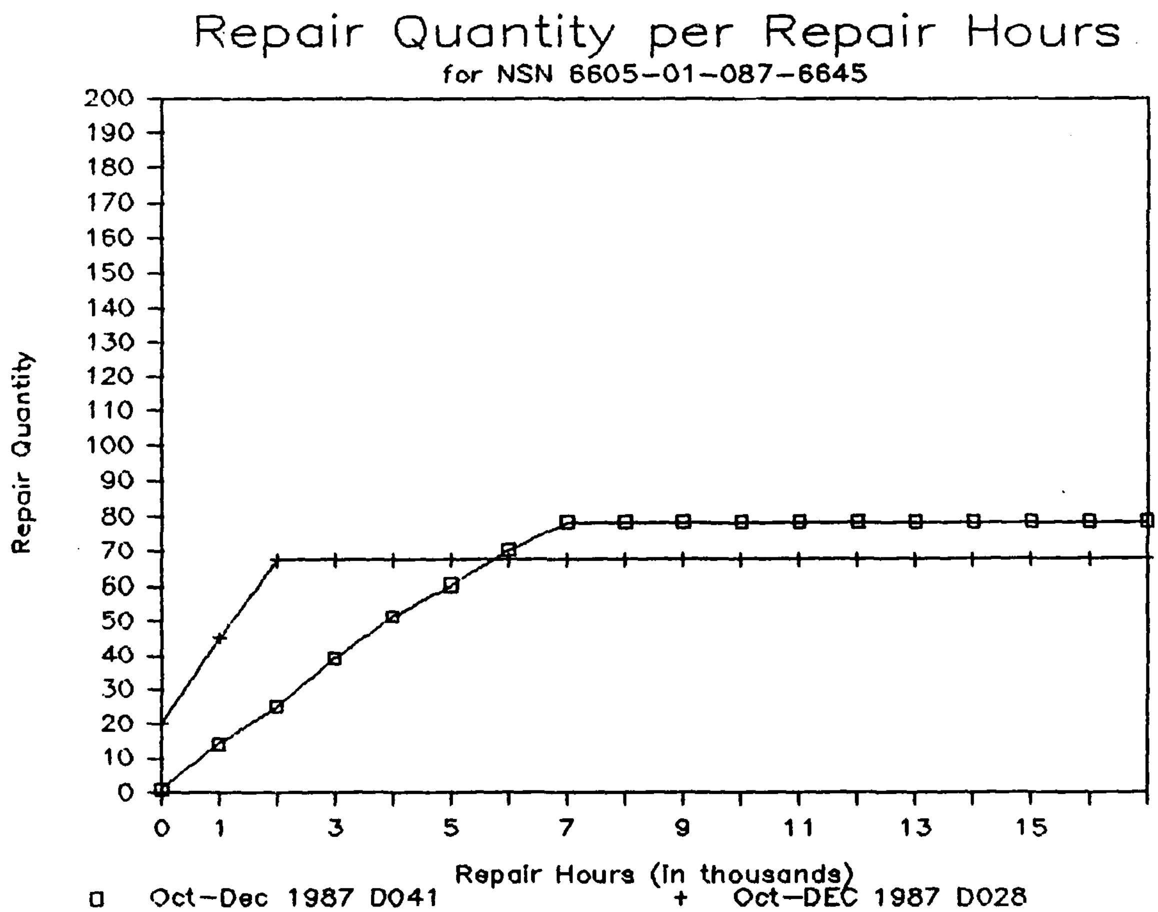

Figure 12. Oct - Dec 1987 Repair of LRU 6605-01-087-6645

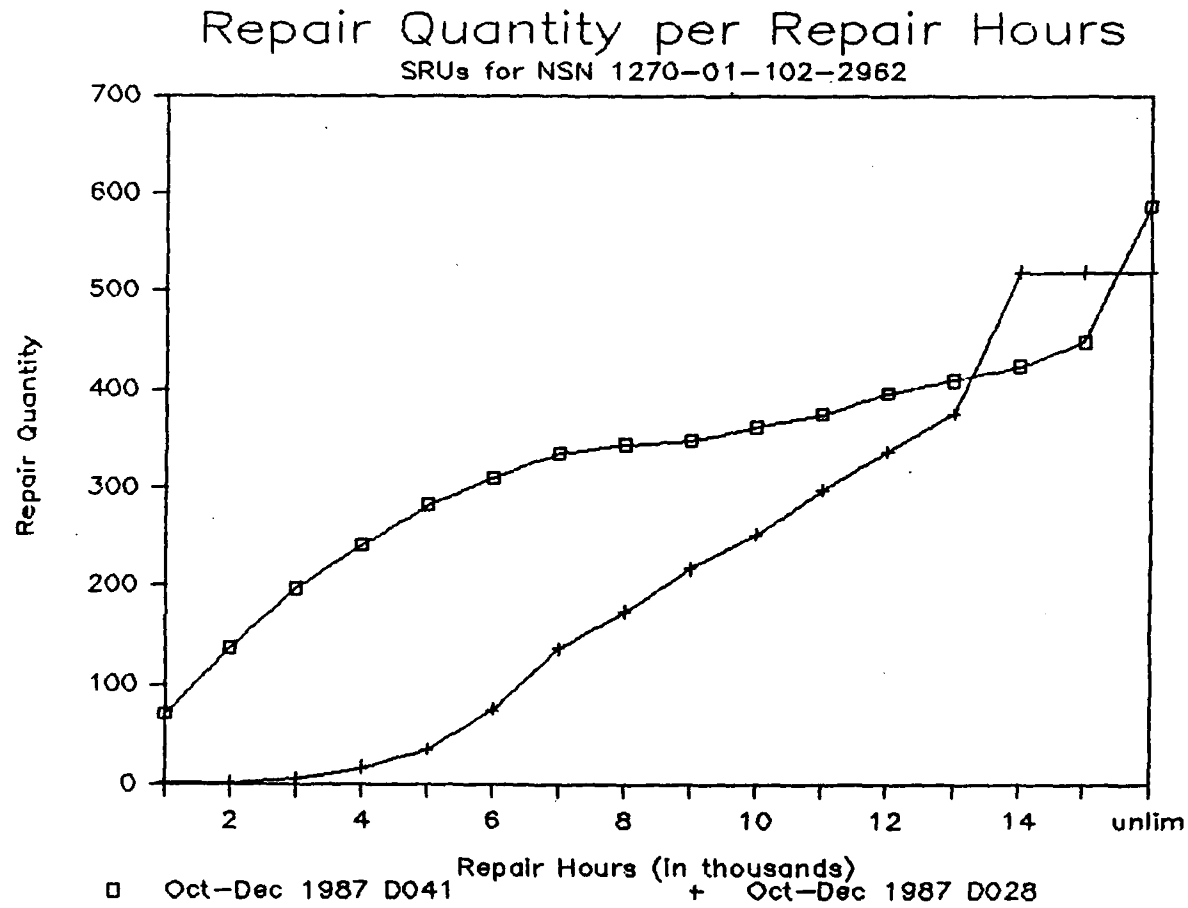

Figure 13. Oct - Dec 1987 SRU Repairs of 1270-01-102-2962

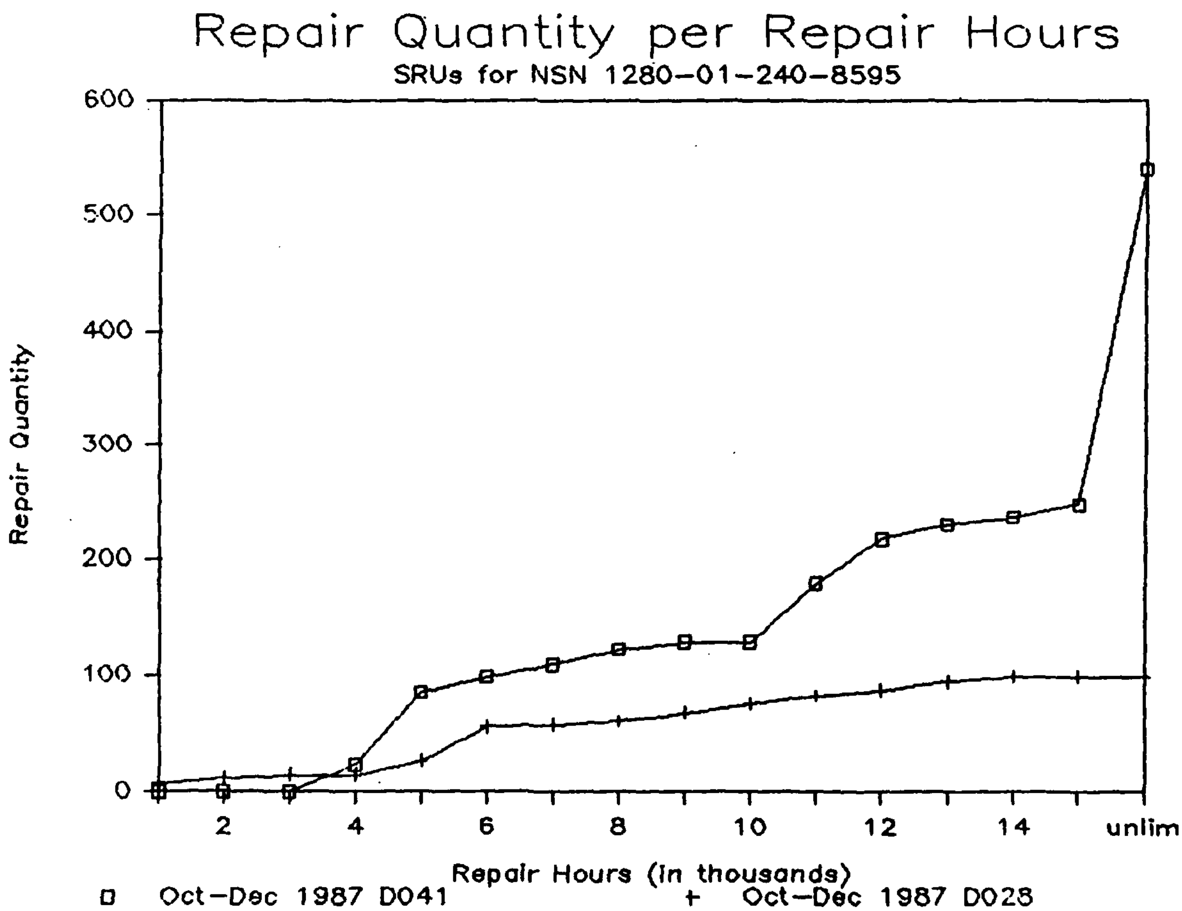

Figure 14. Oct - Dec 1987 SRU Repairs of 1280-01-240-8595

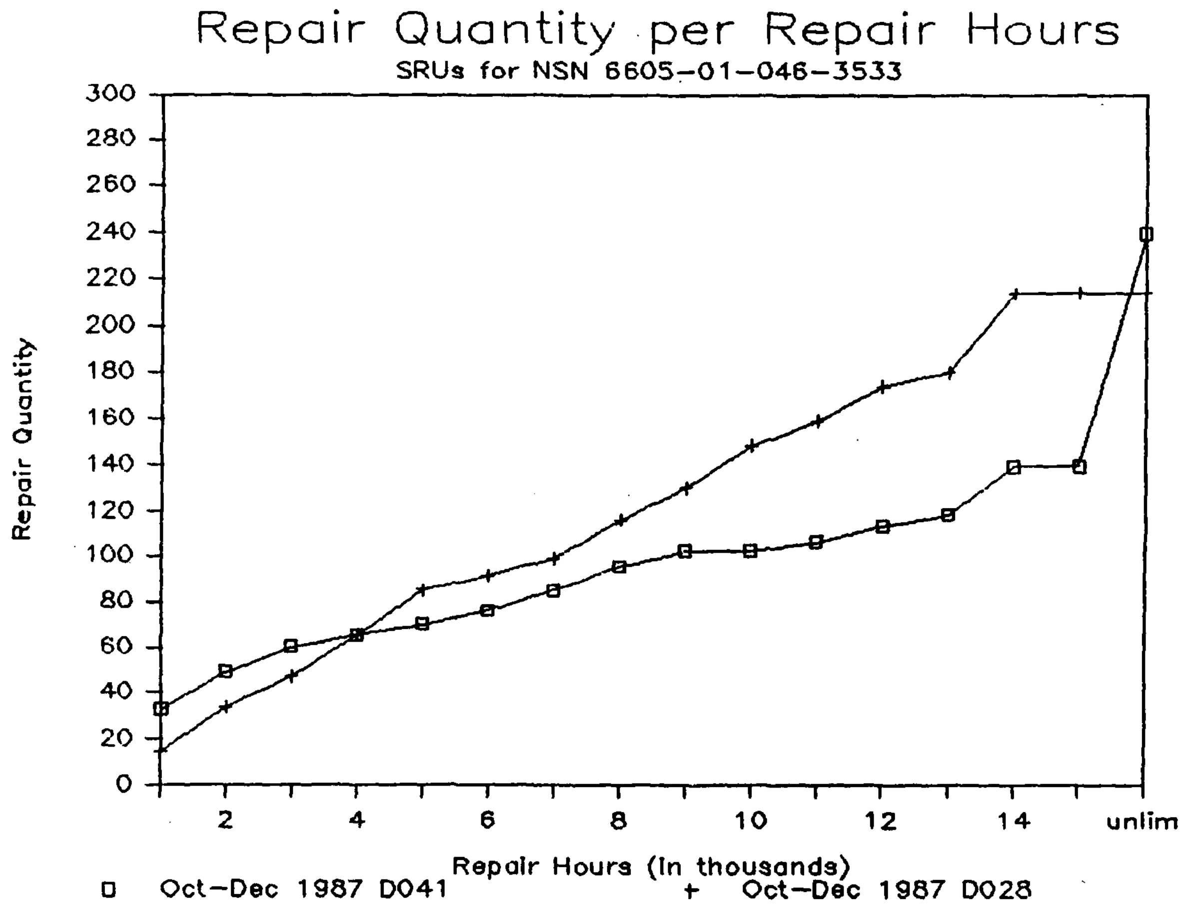

Figure 15. Oct - Dec 1987 SRU Repairs of 6605-01-046-3533

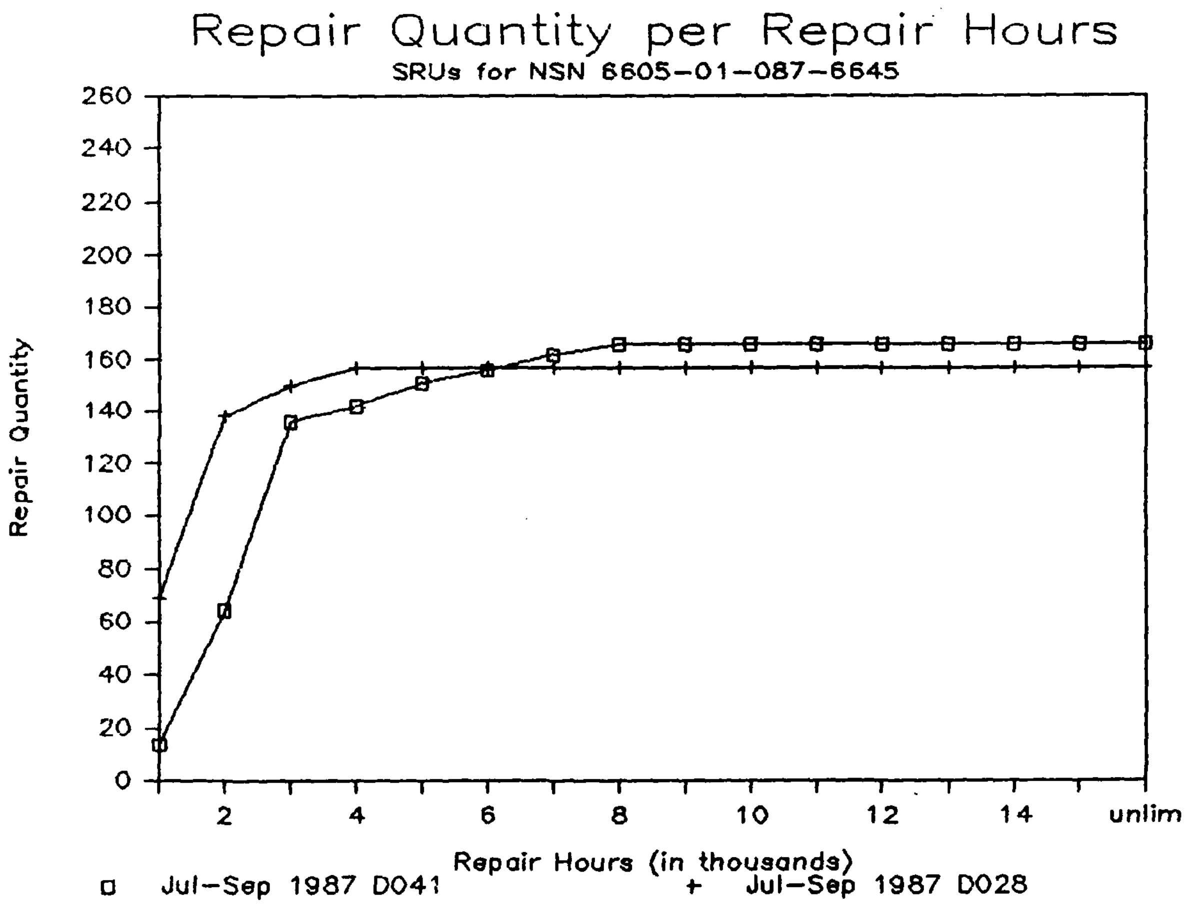

Figure 16. Oct - Dec 1987 SRU Repairs of 6605-01-087-6645

Summary

This chapter revealed that the D028 produced significantly different repair priorities than DRIVE's current forecasting method. The D028 forecasts required fewer repair hours to satisfy the number of LRUs DRIVE recommended for repair. This is most likely a result of incomplete D028 data; the bases with no D028 demands may have reduced the repair requirement beyond the level their actual demands would have recommended. The repair quantities of LRUs and SRUs, based on the D028 demand rates, also vary less than the D041 repair quantities from one quarter to the next. This indicates that the 18 month moving average forecasts are less variable than DRIVE's four-quarter moving average forecast. The analysis also revealed considerable variation between D028 base demand rates; however, the D028 demand rate at a base remains relatively stable between quarters. The D028 18 month moving average appears to dampen the actual base demand rates. The next chapter presents the conclusions of the research and makes recommendations for futher studies.

V. Conclusions and Recommendations

Conclusions

Using base specific demands (D028) in the DRIVE model instead of worldwide demands (D041) to forecast base demands significantly changes the quarterly depot repair priorities. For the third and fourth quarters of 1987, the D028 forecasts recommended less quantities of the critical LRUs for repair but did not recommend less quantities of SRUs for repair across all of the critical SRUs. The D028 forecasts also required fewer repair hours to satisfy the optimal number of LRUs DRIVE recommended for repair. This is most likely a result of incomplete D028 data; the bases with no D028 demands may have reduced the repair requirement beyond the level their actual demands would have recommended. Another possible explanation is that the unusually high demand rate for an item at one base appears to increase the worldwide requirements beyond the level predicted by each base's demands. The repair quantities of LRUs and SRUs, based on the D028 demand rates, also vary less than the D041 repair quantities from one quarter to the next. This indicates that the D028 18 month moving average forecasts are less variable than the four-quarter moving average forecast DRIVE uses.

There is considerable variation between D028 base demand rates; however, the D028 demand rate at a base remains relatively stable between quarters. The D028 18 month moving

average appears to dampen the actual base demand rates. These observations are consistent across all of the LRUs and SRUs at each of the 21 F-16 bases. Since demand varies significantly from base to base, we should get a more accurate picture of each base's demand patterns by using each base's demand rates instead of an average of every base's demands. By taking an average of every base's demands, the DRIVE model does not meet the requirements of the bases with unusually high demands, while the bases with low demands can not justify the requirements that worldwide demand rates set for them. In peacetime, DRIVE may better support the needs of each base by using each base's demand history to forecast demands. During war, when the bases may operate in a totally different environment, an average of several bases' demands may be more appropriate.

Recommendations

This research determined that the DRIVE model is sensitive to the varying demand rates found throughout the Air Force. It was concluded that because demand varies significantly from base to base, DRIVE may better support the needs of each base by using each base's demand history to forecast base demands during peacetime. The following recommendations are intended to aid future studies of DRIVE's forecasting method.

1. AFLC needs to retain a history of actual base demands.
2. Units that have deployed for 30 days, as in a Coronet Warrior exercise, should be included in the DRIVE data base so actual wartime demand rates could be used in DRIVE to assess the effect on aircraft availability of using the D028 to forecast base demands.
3. Future studies should analyze the volatility of the D028 and the D041 forecasts to determine if demand rates need to be reviewed before running the DRIVE model.
4. Single exponential smoothing of base demand rates in DRIVE should be considered in lieu of the D028 and D041 forecasts.
5. Pooling demands of bases with approximately the same number of flying hours should be considered as an alternative forecasting method for DRIVE.

Actual base demand rates need to be retained to accurately assess the impact on aircraft availability of using base demand rates. The D028 data used in this research appeared to be incomplete since some bases had no D028 demand history for some of the LRUs.

Units that have deployed for 30 days, as in a Coronet Warrior exercise, should be included in the DRIVE data base so actual wartime demand rates could be used in DRIVE to assess the effect on aircraft availability of using the D028 to

forecast base demands. Actual wartime demand rates were not available for any of the bases in the DRIVE data base during this research.

Future studies should analyze the volatility of the D028 and the D041 forecasts to determine if demand rates need to be reviewed before running the DRIVE model. Volatility of demands needs to be considered since large variations in repair quantities may be costly and make planning difficult. A base with excessive demand variability, due to random occurrences, may need their demand rate adjusted so DRIVE does not overcompensate them during the next quarter. This research revealed that repair quantities based on D041 demand rates are more volatile than D028 repair quantities. However, this researcher was only able to obtain two quarters of the 18 month averaged demands; the volatility of demand needs to be analyzed over several quarters.

Single exponential smoothing of base demand rates in the DRIVE model should be considered in lieu of the D028 and D041 forecasts. The literature review revealed that exponential smoothing was a better predictor of quarterly demands than a moving average, because Air Force items have time-varying means. DRIVE may need to use a different smoothing constant depending on the forecasting horizon for which it is being used. Sherbrooke recommended a smoothing constant of 0.4 for quarterly demands; however, a lower

smoothing constant may be necessary for short term, (i.e., two weeks), forecasts.

Another alternative forecasting method would be to pool demands of bases with approximately the same number of flying hours. The AFLMC study reported that demands vary less for bases with a similar number of flying hours. This forecasting approach would not rely heavily on the assumption that demand varies linearly with flying hours.

This chapter summarized the conclusions and made recommendations for future studies. More studies of the DRIVE model need to be performed in order to identify other actions which may further improve its logistics decisions and combat capability.

Appendix A: Units Included in the DRIVE Data Base

	Organization	Base	Account
1.	AFFTC	EDWARDS	FB2805
2.	ADTCE	EGLIN	FB2823
3.	363TFW	SHAW	FB4803
4.	56TTW	MACDILL	FB4814
5.	58TTW	LUKE	FB4887
6.	86TFW	RAMSTEIN	FB5612
7.	50TFW	HAHN	FB5620
8.	52TFW	SPANGDAHLEM	FB5621
9.	TTFS	TUCSON	FB6022
10.	FIS159	JACKSONVILLE	FB6091
11.	127TFFS	MCCONNELL	FB6151
12.	FIS186	GREAT FALLS	FB6261
13.	419/388	HILL	FB2027
14.	31TFW	HOMESTEAD	FB4829
15.	347TFW	MOODY	FB4830
16.	474/57	NELLIS	FB4852
17.	401TFW	TORREJON	FB5573
18.	169TFG	MCENTIRE	FB6401
19.	149TFG	KELLY	FB6432
20.	158TFG	BURLINGTON	FB6451
21.	PLSC	KADENA	FB5222

Appendix B: Line Replacement Units in the DRIVE Data Base

Expanded Fire Control Computer
Radar Antenna
Radar Transmitter
Radar Control Panel
Hud Set, Pilots Display Unit
RF Unit Low Power
RF Unit Low Power
RF Unit Low Power
RF Unit Low Power
Hud, Electronic Unit
Processor, Digital Signal GPI
Radar Antenna
Radar Computer
Remote Interface Unit, Conventional SMS
Remote Interface Unit, Missle SMS
Stores Control Panel
Expanded Central Interface Unit, Stores
Indicator, Radar/E-O Display Unit
Electronics Assembly Unit
Remote Interface Unit, Jettison/Release SMS
Fire Control Navigation Panel
Internal Navigation Unit
Accelerometer Assembly, Normal/Lateral
Computer, Central Air Data
Electronic Component Assembly
Rate Gyro Assembly, Flight Control
Pneumatic Sensor
Recorder Assembly, FLCS Data
Panel Assembly, Flight Control
Panel Assembly, Manual Trim
Flight Control Computer Assembly
Flight Control Computer Assembly

Appendix C: Paired Difference Test of an Hypothesis

The paired difference test is used to make an inference about the difference between two population means. In this study, the null hypothesis was that the mean quarterly repair quantities, using forecasting method one and two, were equal. The alternative hypothesis was that the repair quantities were different. The quarterly repair quantities were paired and the difference between the repair quantities from the two forecasting methods were analyzed. The differences in the quarterly repair quantities were regarded as a random sample of all quarterly differences. This sample was used to make an inference about the mean of the population of differences. Thus, the test was (McClave and Benson, 1985:363):

$$H_o: \quad u_1 - u_2 = 0 \qquad H_a: \quad u_1 - u_2 \neq 0$$

The test statistic was a one-sample t statistic since a single sample of differences was analyzed. The one-sample t statistic is calculated as follows: (McClave and Benson, 1985:362)

$$t = \bar{X}_d / S_d / (N_d)^{1/2}$$

where

$\bar{X}_d$ = Sample mean of differences

S_d = Sample standard deviation of differences

N_d = Number of differences

The following assumptions were made in calculating the t statistic:

1. The population of differences in quarterly repair quantities are approximately normally distributed.
2. The sample differences are randomly selected from a population of differences.

The paired difference statistic was used to remove the variability in quarterly repair quantities so the difference between population means could be analyzed. The differencing removed the variability due to the dimension (each quarter) on which the observations were paired. This is an example of a randomized block experiment, where the removal of the variability due to quarterly differences is called blocking (McClave and Benson, 1985:364).

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The purpose of this study was to determine the effect of using base specific demand rates in the DRIVE model. This study compared the quarterly repair lists DRIVE recommended using worldwide demands versus base demands for the F-16A. The research revealed that using base specific demands (D028) in the DRIVE model instead of worldwide demands (D041) significantly changes the quarterly depot repair priorities. The D028 forecasts recommended less quantities of the critical LRUs for repair and they also required fewer repair hours to satisfy the optimal number of LRUs DRIVE recommended for repair. This may be a result of incomplete D028 data; the bases with no D028 demands may have reduced the repair requirement beyond the level their actual demands would have recommended. The repair quantities of LRUs and SRUs based on the D028 demand rates also vary less than the D041 repair quantities from one quarter to the next. This indicates that the D028 18 month moving average forecasts are less variable than DRIVE's four-quarter moving average forecast.

There is considerable variation between D028 base demand rates; however, the D028 demand rate at a base remains relatively stable between quarters. The D028 18 month moving average appears to dampen the actual base demand rates. Since the worldwide demand rates are an average of all of the base's demands, the requirements of the bases with unusually high demands are not met, while the bases with low demands can not justify the requirements that the worldwide demand rates set for them. By taking an average of the highly different base demand rates, the DRIVE model does not properly allocate requirements according to each base's demand history.

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